Mu'tah University 2016   Hala Khaled Al-Masri   An Approach For Enhancing Fingerprinting …

Mu'tah University
College of Graduate studies

An Approach For Enhancing Fingerprinting For Indoor Localization

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A thesis submitted to the College of Graduate Studies in Partial fulfilment of the requirements for the Master's degree in Computer Science to the Department of Information Technology, University of Mu'tah.

Mu'tah University, 2016

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بالضرورة عن وجهة نظر جامعة مؤتة

بسم الله الرحمن الرحيم

MUTAH UNIVERSITY
College of Graduate Studies

جامعة مؤتة
كلية الدراسات العليا

نموذج رقم (14)

قرار إجازة رسالة جامعية

تقرر إجازة الرسالة المقدمة من الطالبة هلا خالد عبدالمنعم الموسومة بـ:

An Approach for Enhancinzg Fingerprinting for Indoor Localization

استكمالاً لمتطلبات الحصول على درجة الماجستير في الحاسوب.

القسم: تكنولوجيا المعلومات.

	التوقيع	التاريخ	
د. بسام محمد المحادين		28/7/2016	مشرفاً ورئيسا
د. أحمد حمد العبادلة		28/7/2016	عضواً
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ACKNOWLEDGMENT

I would like first to dedicate this thesis to memory of my beloved father and to my beloved mother.

I would also like to thank my supervisors Dr. Bassam Al Mahadeen and Dr. Ahmad Al Abadleh for their continuous guidance, support and encouragement to accomplish this work. I would also like to offer special thanks to them for their valuable suggestions, and comments. They consistently allowed this thesis to be my own work, but steered me in the right direction whenever they thought I needed it. The door to Dr. Mahadeen and Dr. Abadleh office was always open whenever I ran into a trouble spot or had a question about my research or writing. Without their continued support I would not be working on this exciting research topic.

I would also like to offer my sincere thanks to all the members of IT department, and unity of admission and registration, who did not hesitate to provide help during conducting real experiments for my thesis. I would also like to thank all my colleagues in work and study, especially Mrs Sawsn Al-Hujoj and Mrs Seham Al-Hajaya, who have always been there for me.

Finally, I must express my very profound gratitude to my beloved mother and to my sisters and brothers, for providing me with unfailing support and continuous encouragement throughout my years of study and through the process of researching and writing this thesis. This accomplishment would not have been possible without them. Thank you.

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Abbreviations

LBS	Location Based Services
GPS	Global Positioning System
Wi-Fi	Wireless Fidelity
APs	Access Points
RSS	Received Signal Strength
MAC	Media Access Control
GNSS	Global Navigation Satellite System
IPS	Indoor Positioning System
RM	Radio Map
AOA	Angle Of Arrival
TOA	Time Of Arrival
TDOA	Time Difference Of Arrival
WLAN	Wireless Local Area Network
PDAs	Personal Digital Assistants
IPOS	Indoor Positioning System
ED	Euclidian Distance
IRIS LPS	Infrared Indoor Scour Local Positioning System
TOF	Time Of Flight
RP	Reference Point
EAS	Electronic Article Surveillance
UWB	Ultra Wide Band
LOS	Line Of Sight
SSID	Service Set IDentifier
BSSID	Basic Set IDentifier
St. D	Standard Deviation
KNN	K Nearest Neighbour
ADSL	Asymmetric Digital Subscriber Line
BHS	Bridge Head Server
DSLAM	Digital Subscriber Line Access Multiplexer
WAPs	Wireless Access Points

Abstract

An Approach For Enhancing Fingerprinting For Indoor Localization

Hala Khaled Al-Masri

Mu'tah University, 2016

Indoor positioning systems attracted the attention of researchers in indoor localization field. There are some drawbacks which still need to be resolved. First, GPS technology has proven itself as a successful technology for outdoor localization, but it is not suitable for indoor localization, since the satellite signals cannot penetrate the walls or roofs of buildings. Second, some of indoor localization approaches which depend on Wi-Fi signal have problems with signal attenuation which affects the system accuracy.

This thesis proposes an indoor localization approach, which depends on received signal strength from access points which are distributed inside the building, as well as, acceleration and direction from Smartphones sensors, 3-axis accelerometer and orientation respectively, in order to track the users and determine their positions. The proposed approach addresses the limitations of a promising indoor positioning technique which is called fingerprinting technique, such as the effort of building the radio map, the size of database, the energy consumption and the calibration. The proposed approach has two phases, offline and online phases. In offline phase, all sections (Rooms and Corridors) inside the building are surveyed depending on people's movement pattern when they enter into the sections, in order to store the acceleration, direction and received signal strength readings as a unique signature for each section called offline signature in the signatures map. In online phase, the users can detect their positions using Smartphone, through recording the acceleration, direction and received signal strength readings, which form the online signature, then comparing it with all offline signatures using new proposed algorithm called lookup algorithm in order to determine the users' positions.

The proposed approach is tested inside different types of buildings using real experiments, which illustrate that combining the direction and acceleration with received signal strength reduces the time and cost which are consumed when the users' positions are determined, and minimizes the effects of calibration process that is usually required in fingerprinting approaches because of signal attenuation problems. So, the proposed approach outperformed the fingerprinting approaches in terms the overall accuracy.

Keywords: *Fingerprinting, received signal strength, direction, offline signature, online signature.*

الملخص

طريقة جديدة لتحسين نظام البصمات لتحديد المواقع بالأماكن المغلقة

هلا خالد عبد المنعم المصري

جامعة مؤتة، 2016

إنّ أنظمة تحديد المواقع في الأماكن المغلقة جذبت اهتماماً كبيراً من قبل الباحثين في مجال تحديد المواقع. حيث لا تزال هناك بعض السلبيات بحاجة لحل في هذا المجال. أولاً تكنولوجيا (GPS) أثبتت نفسها على أنها تقنية ناجحة لتحديد المواقع خارج المباني، لكنها ليست مناسبة لتحديدها في الداخل، لأن إشارات الأقمار الصناعية لا يمكن أن تخترق جدران أو أسقف المباني. ثانياً، بعض طرق تحديد المواقع في الأماكن المغلقة التي تعتمد على إشارة (Wi-Fi) لديها مشاكل في ضعف الإشارة مما يؤثر على دقة النظام.

إنَّ هذه الرسالة تقترح طريقة جديدة لتحديد المواقع في الأماكن المغلقة يعتمد على قوة الإشارة المستقبَلة (RSS) من نقاط التوصيل (APs)، وكذلك، التسارع والاتجاه من أجهزة استشعار الهواتف الذكية (3-axis accelerometer and Orientation) على التوالي. وذلك بهدف تتبع المستخدمين وتحديد مواقعهم.
الطريقة المقترحة تعالج القيود المفروضة على تقنية واحدة لتحديد المواقع بالأماكن المغلقة تسمى تقنية البصمات (Fingerprinting)، مثل الجهود التي تبذل لبناء قاعدة البيانات، الحجم الكبير لقاعدة البيانات، الطاقة المستهلكة لبناء هذه القاعدة، بالإضافة إلى إعادة تجميع البيانات من وقت لآخر (Calibration) .

الطريقة المقترحة تتكون من مرحلتين (offline and online phases). مرحلة (offline) جميع الأقسام داخل المبنى يتم مسحها اعتمادا على أنماط حركة الأشخاص عند دخولهم لهذه الأقسام بهدف تخزين قراءات التسارع والاتجاه وقوة الإشارة المستقبَلة (RSS) كتوقيع فريد في قاعدة البيانات يسمى (Offline signature). مرحلة (Online) يمكن للمستخدمين الكشف عن مواقعهم باستخدام الهاتف الذكي، من خلال تسجيل قراءات التسارع، الاتجاه وقوة الإشارة المستقبَلة، التي تشكل (Online signature)، ثم مقارنة (Online signature) مع جميع (Offline signatures) بهدف تحديد مواقع الأشخاص من خلال الخوارزمية المقترحة (Lookup algorithm).

تم اختبار الطريقة المقترحة داخل أنواع مختلفة من المباني باستخدام عدة تجارب أوضحت أن الدمج بين الاتجاه والتسارع مع قوة الإشارة المستقبَلة قللَ من الوقت والتكلفة التي يتم استهلاكها عندما يتم تحديد مواقع المستخدمين، كما وقلل من تأثير عملية (Calibration) المطلوبة عادة في المنهجيات التي تعتمد نظام البصمات لتحديد المواقع بسبب مشاكل ضعف الإشارة. لذلك، فإنّ الطريقة المقترحة تفوقت على الطرق الأخرى التي تعتمد نظام البصمات من حيث الدقة الشاملة.

Chapter One: Introduction

1.1 Overview

The positioning technology is one of the major issues for Location Based Services (LBS). The indoor positioning precision requirement is higher than that for outdoors (Ferraro, R., et al., 2011), (Chen, L., et al., 2013).

Global Positioning System (GPS) is an ideal choice for outdoor localization. However, GPS is not suitable for indoor localization, since the satellite signals cannot penetrate buildings walls or their roofs (Li, B., et al., 2006), (Li, B.,et al., 2011). Furthermore, when the GPS technique is used, the errors for positioning may have tens of meters (Bing, B., et al., 2003).

Wi-Fi (Wireless Fidelity) has been widely used for indoor localization. The Wi-Fi technology provides local access to a fixed network that leads to wider dissemination, low cost and a rapidly rising for indoor localization. Using existing infrastructure for positioning seems an excellent option. Moreover, Received Signal Strength (RSS) measurements by the Smartphones from the Access Points (APs) that are distributed inside buildings are available for positioning. However, an indoor positioning system should take into account RSS from wireless APs, which are widely used and available in the public environments such as airports and shopping malls. An Indoor Positioning Systems (IPS) is extremely valuable in numerous applications, for example, tracking systems for elders or individuals inside living rooms, indoor robotics, parking lots, shopping mall and so forth. While outside environment utilizing Global Navigation Satellite System (GNSS) and cell system function admirably, and across the board utilized for route. In spite of, there is an issue with signals spread from satellites or cell site; they cannot be utilized inside building zones or even in an urban situation (Torteeka, P., et al., 2014).

To sum up, Individuals invest roughly 70% of their time inside. Therefore, understanding the indoor environments is subsequently essential for an extensive range of developing multipurpose individual and social applications (Jiang, Y., et al., 2013).

Indoor localization using Smartphones has been generally examined, and its significance is consistently expanding as an aftereffect of the various applications that require indoor localization systems. Consequently, IPS is introduced to track things or individuals inside a building. The commonness of mobile phones and spread of computerizing inspires broad exploration on wireless indoor localization (Wu, C., et al., 2012). In the condition of the IPS,

numerous technologies have been proposed. In general, they involve three techniques : triangulation, trialtertion, and fingerprinting. Triangulation is one of the IPS techniques, which relies upon geometric characteristics of triangles to evaluate the user's position (Torteeka, P., et al., 2014). Trilateration is another type of IPS techniques that obtains the position as the intersection between the three circles formed by computing the distances between target node and three reference nodes (Yang, Z., et al., 2010). Fingerprinting method is one of the popular IPS techniques, a site survey should be conducted in advance to collect the signals, such as wireless signals in order to build a database that is called a Radio Map (RM) (Wu, c., et al., 2012).

Fingerprinting strategy comprises of two phases: offline phase, where the data is gathered by surveying the building, and online phase, where the measured signals are compared with the signals in the RM (Liu, H., et al., 2014). Multipath issue, which implies that the signals originate from different directions, has less impact on fingerprinting strategy. For that the database is worked for a timeframe, which makes the data more robust. In addition, fingerprinting strategy can supply more accurate and precise position. However, the database which is stored in the RM must be enough, in order to reach a specific end goal to achieve an accurate and precise position. Moreover, the database must be modernized when the environments change to a great range (Yu,L., et al., 2011). A lot of manual effort, time and cost are required, pending adjustment for gaining a huge training samples. Fingerprinting technique has turned into the most prominent IPS techniques for some reasons: First, extra equipment is not required. Second, the RSS is generally utilized as a part of the base networks. Third, it supplies high ratios of exactness (Torteeka, P., et al., 2014).

Recently, the IPS became very important system. A comprehensive study for IPS performance and techniques has led the research to a critical point, known as reducing the time and efforts that the system spends during the offline phase and enhancing the overall accuracy.

This thesis presents an approach based on fingerprinting with Smartphone sensors. The rationale base behind the proposed approach is that; most of the people have the consistent movement patterns when they enter the building sections (e.g. rooms and corridors). The consistency of user's walking during their daily life is a significant factor that can be used in order to detect the user's position. In our approach the Smartphone sensors are used in order to collect the accelerations and directions, also the already existing wireless

infrastructure is used to collect the RSS readings, so has no need of any extra hardware.

Our proposed approach consists of two main phases, the offline phase and the online phase. The result of offline phase stored in the database as a signature for each section called offline signature, (we will use this term hereafter to represent the signature map which stored in the database). While the result of online phase called online signature, (we will use this term hereafter to represent the signature which is formed in online phase). The online signature will be compared with the offline signatures, then the user's position is determined by the new proposed algorithm in our approach which is called lookup algorithm.

1.2 Research Importance and Motivation

People spend most of their time in indoor environments (Chon,Y., et al., 2011), because of that, the need to localize their positions in such environments have been increased. GPS technology can be used to give an accurate result for the user's position in outdoor environments. Nevertheless, GPS can not be utilize in indoor environments since the signals are unreliable or inaccessible. Conversely Wi-Fi technology is widely used in indoor environments and can be used to determine the users' positions in such environments instead of GPS technology. The main motivations and importance for our research are listed in the following points:

1. The need to get an accurate results of detecting positions of users within the use of indoor localization and Smartphone sensors depending on room level accuracy.
2. The need to make the localization for indoor environments available by building the signature whenever an individual enters a place automatically within the use of Smartphones.
3. The need to use for commonly tools in the integration of indoor positioning techniques. Where, recently there is nothing more common as much as Smartphones. The Smartphone sensors can be used with RSS that are collected from APs to build an effective approach. Where, the acceleration in the corridors is more consistant than the rooms, and it devolve to zero when the user's movement status is stationary. On the contrary, when he/she is moving. While, the direction is almost regular on the corridors and irregular in the rooms. Plus the fact, the rooms that are close to each other and have opposite direction has completely opposite different value in direction, even if they have similar RSS or acceleration.

4. The need to contribute in publishing such a powerful study that illustrates accurate results that can outperform other studies within the same field of interest.

1.3 Research Aims and Objectives

The proposed approach aims to decrease the effort and time that are spent during the offline phase and enhancing the overall accuracy to detect the user's position. To sum up, the main aim is intended to be achieved here is to save the effort, time, and energy that are spent during building the database in the offline phase. The other aim is to enhance the accuracy of the IPS by giving an accurate position for users inside building using simple search algorithms. This can be achived taking in consideration the following objectives:

1. **Comprehend the signal features and focusing on impairment of Wi-Fi signal power.**

Understanding the signal components with an emphasizing on the limitations of Wi-Fi signals, such as multipath problem and signal attenuation.

2. **Conduct real experiments to analyze and measure the signal features and the readings of Smartphone sensors with a focus on existing approach to get good accuracy in our approach.**

Utilize a results of real experiments to explain and measure the signal informations, in addition to the readings of 3-axis accelerometer sensor and orientation sensor, with an emphasis on existing way to acquire great precision in our approach.

3. **Improve overall accuracy to determine an accurate user's position by defining best locations for APs and form a signatures for all sections. (Room or Corridor) of building.** Note: the (Room or corridor) will be called as section hereafter.

Enhance an accuracy to decide a precise user's position by determining best APs situation inside the building, in addition, construct unique signature for each section of building.

4. **Evaluate IPS accuracy using the proposed approach, then comparing it with other approaches in the same field.**

Assess IPS accuracy utilizing the approach that proposed as a part of this work, then compare it with respect to different approaches that presented in indoor localization field.

1.4 Problem Statement

Fingerprinting approach became the most popular indoor localization approach due to its good accuracy (Bahl, P., et al., 2000). However it still suffers from various problems: first, the huge effort that is needed to build the database which consumes a big amount of energy. Second, the huge database needs complex searching algorithms. Third, the attenuation problem in Wi-Fi RSS which makes the accuracy drops significantly. For these reasons, we proposed an approach based on fingerprinting technique which relies on different factors, in order to minimize the efforts of building the database, reduce the size of the database, reduce the amount of searching time when the user's position is determined and avoid the problems in RSS.

1.5 Research Questions

1. How to minimize the size of database and minimize the effort of building this database?
2. How to solve the attenuation problem in Wi-Fi RSS which makes the accuracy drops significantly like outliers RSS?
3. How to discover the acceleration and direction to be combined with RSS in order to contribute in accomplishing strong and accurate results?
4. How to overcome the issues of the noisy sensors and the noisy RSS?

1.6 Research Contribution

The thesis proposes a new approach to localize users in indoor environment, based on RSS and Smartphone sensors in order to form a unique signature for each section inside the building. Formation the signature helps to retrieve the exact users' locations in room level accuracy early in the process, and then detect accurate users' positions. In addition, the contributions of this thesis are highlighted here as follows:

1. Making a complete study about the effect of signals and sensors data.
2. Reducing the effort of building the database.
3. Reducing the size of the database.
4. Minimizing the energy consumption.
5. Conducting the real experiments in different indoor environments.
6. Getting a comparable accuracy.

7. Minimizing the needed effort of the calibration process, which means rebuild the RM database from time to time due to signal attenuation and scattering, which needs a considerable measure of effort.

1.7 Thesis Structure

Firstly, in this chapter, we have introduced the research background, research problem, and purpose within exposing the main reasons behind carrying out this research. The rest of thesis is organized as follows.

The remaining chapters are presented in this thesis as follows. In chapter two, we will review the previous studies and literature relating to our research in term of both the technology used and the desired aim from employing each proposed technique within each overviewed work.

In chapter three, we will present the research methodology that was employed for this research, including the proposed approach, methods, and algorithms to answer the research questions, also achieve its proposed aims and the expected research outcomes.

Chapter four presents a detailed explanation of the experimental setup and results obtained from the proposed approach. Also, presents summarizes the conclusion, and future works as well as researcher recommendations.

Chapter Two: Literature Review

2. 1 Overview

The GPS is a constellation of 24 well-spaced satellites that orbit the Earth, offers perhaps the easiest way to locate a geographic location for the user in outdoor. The positioning accuracy of GPS receivers ranging from 7 to 10 meters (m) (Lim, H., et al., 2005). Despite many advantages of GPS, but it is not well suited for indoor environments, because the structure of the building easily prevents the arrival of satellite signals, this mean the signal strength is too low to penetrate a building. So GPS cannot be used in indoor environment, since it is insufficient, and does not operate efficiently indoor (Chen, G., et al., 2000).

Deployment widely of the 802.11 infrastructure and the Wi-Fi embedded devices is the most convincing reason for indoor localization based on radio frequency. Indoor localization systems can be classified based on the signal types (e.g. infrared, radio frequency), signal metrics (e.g. AOA: Angle of Arrival, TOA: Time of Arrival, TDOA: Time Difference of Arrival and RSS) and the metric processing techniques called indoor positioning system techniques (e.g. triangulation, trilateration and fingerprinting) (Lim, H., et al., 2005).

The incentive behind research and development of indoor positioning is the success of locate the user in outdoor. Some existing indoor positioning is presented in this part, in order to demonstrate that the indoor positioning has been successful.

The First Wireless Local Area Network (WLAN) based on positioning system is RADAR, developed by (Bahl, P., et al., 2000) and used the fingerprinting technique. Depending on nearest neighbour algorithm RADAR gave an error distance ratio ranging between 3-5 m. The error distance ratio was reduced to 2.37 m by (Bahl, P., et al., 2000) using a Viterbi-like algorithm in the RADAR.

(Ekahau., 2002) proposed a system for indoor positioning based on RSS values from APs, the software is commercially available. This system used the triangulation for locating any Wi-Fi enabled device, the accuracy of the system depends on the environment, and it is varied from 1 to 5m. In addition, it works over Personal Digital Assistants (PDAs), standard WLAN, tags in real time, and tracks laptops.

(Otsason, V., et al., 2005) proposed an algorithm for positioning system in Multi-Storey buildings, the accuracy of the system was 5m, Nokia research center developed the algorithm, it is a mobile based robust indoor positioning algorithm; informed that the mobile device based on WLAN technologies and pre infra-structure.

(Retscher, G., et al., 2006) used the RSS fingerprints in order to develop the Indoor Positioning System (IPOS) for indoor environments. The main goal of IPOS is to determine whether the user is inside the room or not, depending on room level accuracy.

(Teuber, A., et al., 2006) achieved positioning accuracy up to 4.47 m using Euclidian distance (ED). They decreased the accuracy to 3 m by applied minimal Euclidian distance and Fuzzy logic post processing together.

In addition to the results of studies that have been displayed above, also there are many recent studies have proved the success of indoor localization with high positioning accuracy, likewise the proposed approach has achieved a promising accuracy for detecting the user's position depending on fingerprinting technique. This is a good evidence of the success of indoor positioning depending on the classifications of indoor localization system, which is mentioned above. Perhaps the most important of these classifications, are the indoor positioning system techniques. So in this chapter we will highlight the most popular indoor positioning techniques that have been into use in the current systems, such as triangulation, trilateration, and fingerprinting. All of them are discussed in details including their applications and importance. Also, the discussion of the limitations of these techniques is presented, and finally the summary is shown.

2. 2 Indoor Positioning System Techniques

Indoor positioning system techniques have been developed rapidly throughout the last years due to its utilization in numerous applications. Indoor positioning localization techniques use signal metrics (e.g. AOA, TOA, TDOA, and RSS) and readings of Smartphone sensor, in order to locate the position using either angle estimation or distance. The fingerprinting and trilateration techniques need to compute the distance, while, the triangulation technique needs angle estimation, in order to locate a position.

The fingerprinting technique consists of two phases; Offline and online phases, in the offline phase, a database of RSS fingerprint is created by recording a large number of RSS in known locations inside the building, while

in the online phase, the measured real time RSS fingerprint match with the RSS fingerprints in the database and determine the closest position by using a searching algorithm or some position based algorithms, and RSS is ordinarily utilized as a part of database (Mestre,P., et al., 2013).

Trilateration is a technique that requires the distances from various reference nodes, at least three reference nodes, in order to obtain the position as the intersection between the three circles which are formed. The distance is calculated by increasing the radio signal speed and the travel time, and usually TOA and TDOA utilized for distance measuring in this technique (Yang, Z., et al., 2010). On the other hand, triangulation technique requires at least two reference points and angle estimation between the transmitter and receiver, in order to obtain the position, and ordinarily AOA utilized for angle estimation (Niculescu, D., et al., 2003), (Roshanaei, M., et al., 2009).

The target of next subsections is to present the indoor positioning techniques, and trade-off them with respect to each others, in order to uncover the importance of the proposed approach.

2.2. 1 Triangulation

Triangulation technique uses the geometric properties of triangles, the aim of that is to estimate the targeted object's location.

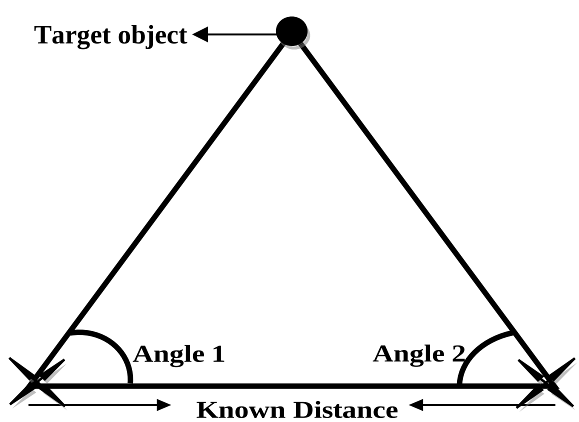


Figure 2.1: Triangulation: the estimated location is determined with the target node and the angles formed by two reference points (Ballazhi, R., 2012).

This technique determines the angle of incidence at which signals arrive at two known reference points, in order to find the object location. The target

object can be found as the third point of a triangle with two angles and one known side (Ballazhi, R., 2012).

Figure (2.1) illustrates how to estimate location using triangulation technique, the triangulation represents in measuring the AOA of at least two reference points. The estimated position corresponds to the intersection of the lines defined by the angles. So, the AOA in triangulation techniques is uses as measuring technique (Disha, A., 2013).

In AOA the Wi-Fi enabled device's signal to receive signals from multiple reference points. The reference point have additional equipment, in order to determine the compass direction, which is indicates from which the user's signal is arriving. Using two reference points the location of the device can be determined. So the position of the target can be derived using at least two reference points and two measured angles (THUMMALAPALLI, S., 2012).

The main observation of using AOA in positioning is the following: The position of the interior point can be determined, if the positions for the vertices of a triangle, and the angles at which an interior point "finds" the vertices are known. This called triangulation, is somewhat resemble to the trilateration. The difference is that the interior point instead of knows the distances to vertices, it knows angles towards triangle sides. The main disadvantages of AOA are large and complex hardware requirements, in addition every reference point needs to have an equipment upgrade.

In Figure (2.2), the position can be identified using triangulation, if beside coordinates of A, B and C, node D knows the angles ADC, CDB, BDA. While if it knows distances AD, BD and CD, the position can be inferred using trilateration. The position is determined by finding the intersection of the three circles determined by the known angles and the landmarks. From several landmarks some Information are acquired, and can be used to get at least square error solution, since, in the general, the measurements of AOA do not have perfect accuracy (Niculescu, D., et al., 2003).

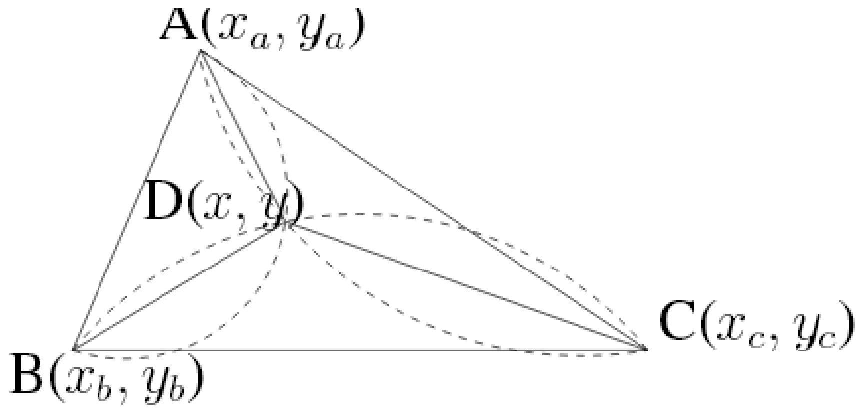


Figure 2.2: Triangulation: Positioning by measuring angles to landmarks (Niculescu, D., et al.2003)

Figure (2.2) shows three reference points A, B and C, which are used their coordinates and angles which are formed from intersections with D, in order to estimate the target position which represents D in the figure.

The triangulation technique is used in some indoor positioning systems, in order to estimate the position. One of these systems is Infrared Indoor Scour Local Positioning System (IRIS LPS) (Aitenbichler, E., et al., 2003) is an optical IR local positioning system. The main idea of this system is receive the IR signals from a tag carried by a target object by stationary mounted stereo cameras, in order to measure the AOA, and then calculate the location of the tag by triangulation technique.

The other one is Active Bat positioning system (Woodman, O. J., et al., 2010) created by researchers at AT&T Cambridge, the system provides orientation information and 3-D position, for the tags which are tracked. The Active Bat System uses triangulation location technique and ultrasonic technology, in order to measure the location of a tag which is carried by a user. A tag regularly broadcasts a short pulse of ultrasound. The short pulse which is broadcasting from the tag is received by a matrix of receivers at known positions. The distances between the tag and the receivers can be measured by the ultrasonic waves, because the tags are below the receiver matrix. So, the distance between a tag and three receivers is needed to calculate the 3-D position of the tag based on the triangulation and principle of multilateration (Ward, A. et al., 1997).

2.2. 2 Trilateration

Trilateration is a technique that requires the distances of three reference nodes to obtain the position as the intersection between the three circles which are formed (Yang, Z., et al., 2010). The trilateration technique determines the coordinates of the target object, in order to estimate the target location, using at least three reference nodes with known coordinates.

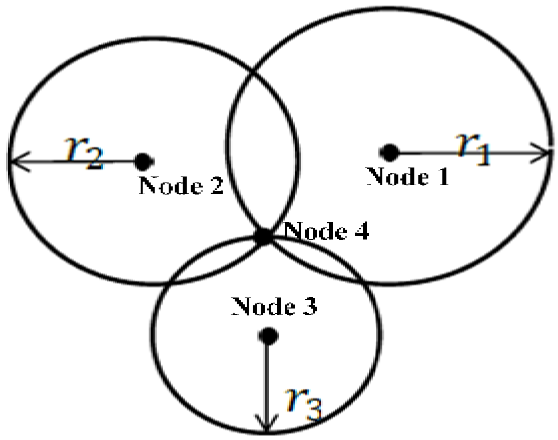


Figure 2.3: Trilateration: The estimated location corresponds to the intersection point of three circles.

Figure (2. 3) shows how estimate the position of the target by compute the distance between the target node and another three reference nodes at least (r1, r2, and r3). Target node position is obtained by the intersections of three circles as shown in the figure. (Disha, A., 2013) The distances (r1, r2 and r3) are computed by Equation (2.1) (Rui Zhou., 2006), (Farahani, S., 2011), then in order to determine (X_4, Y_4) the Equation (2.2) is used (Rui Zhou., 2006), (Farahani, S., 2011). So, in order to find the position of an object or target nodes based on trilateration techniques, the following things have to be available: First, the distances between the object and three different known nodes. Second, the coordinates of these three reference nodes (THUMMALAPALLI, S., 2012).

$$r_i^{\,2} = (X_i - X_4)^2 + (Y_i - Y_4)^2 \qquad \textbf{Equation (2.1)}$$

Where,

r_i is : distance between reference node i and node 4 (target node).

(X_i, Y_i) is: coordinates for reference node i, where i= 1,2,and 3.

(X_4, Y_4) is : coordinates for target node.

$$\textbf{Target node coordinate} = \begin{bmatrix} (X_1 - X_4)^2 + (Y_1 - Y_4)^2 \\ (X_2 - X_4)^2 + (Y_2 - Y_4)^2 \\ (X_3 - X_4)^2 + (Y_3 - Y_4)^2 \end{bmatrix} - \begin{bmatrix} r_1^{\,2} \\ r_2^{\,2} \\ r_3^{\,2} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \quad \textbf{Equation (2.2)}$$

TOA and TDOA are most popular methods utilized for distance measuring in the trilateration technique (Yang, Z., et al., 2010). The TOA method, require to know the time of arrive the signal relative to the emitting time by the receiver. In this case, the receiver must know the time when the signal was emitted. While using TDOA method, the transmitters emit their signals at the same time, so the receiver can measure the time difference between their arrivals (Sanchez, A., et al., 2009).

2.2. 3 Fingerprinting

The fingerprinting technique is extensively used in indoor positioning system. The main reasons of its deployment are the low cost of the user hardware, it does not require any special hardware, it just requires Smartphone and APs, and because it offers a promising performance for indoor positioning (Chen, L., et al., 2013).

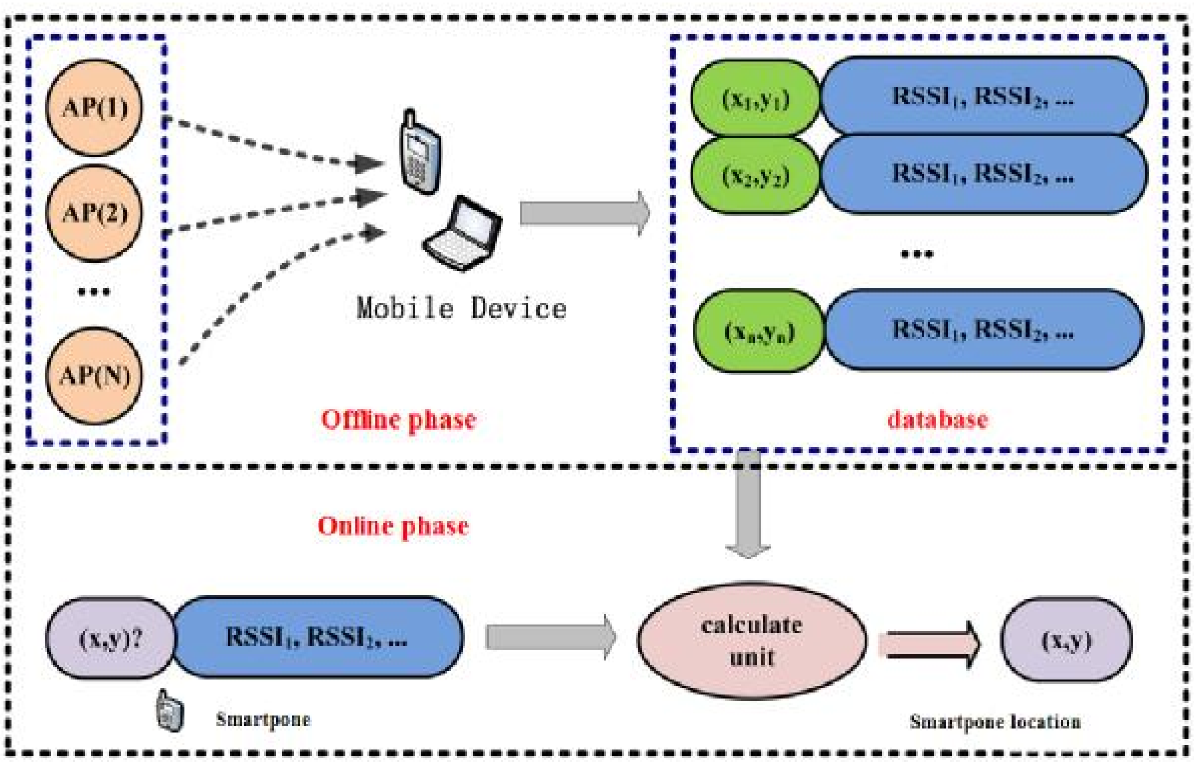


Figure 2.4: Location fingerprinting technique (Chen, L., et al. 2013).

Figure (2.4) shows the Wi-Fi location fingerprinting technique, which is composed of two phases: the offline phase and the online phase. The goal of the offline phase is to build a fingerprint database which is called RM. To generate the RM in a conventional way, some reference points (RPs) in the interested area are determined, next locating a Smartphone at location of one RP, then the RSS readings in this RP are measured from all the APs, after that the RP characteristic feature is selected from these measurements, finally stored it in the database. This process is repeated until measured the RSS readings in all RPs which are determined inside interested area. While in the online phase, the Smartphone measures the RSS readings at a place which it requires its position. The measurements which are including the RSS readings and Media Access Control (MAC) address for each AP are compared with those in the database using a searching algorithm. Ordinarily, the distance is computed based on RSS in order to acquire accurate position. The smallest value of distance indicates the best match, and the likeliest location of the Smartphone can be located (Roos, T., et al., 2002), (Wang, Y., et al. 2003).

The main concern of researchers in the indoor localization field is to increase the accuracy for the IPS techniques such as fingerprinting technique. (Kumar, S., et al., 2014) proposed an indoor localization system to achieve high accurate position using mobile device. The system does not need any specialized infrastructure.

The presence of distinct locations with similar signatures is the basic reason for the existence significant errors up to 8m. A peer assisted localization approach is proposed to achieve more accurate localization by mapping the locations of peer phones with each others (Liu, H., et al., 2014).

WILL proposed an approach by (Wu, c., et al., 2013) to eliminate the site survey in order to reduce the effort for construct RM. WILL achieves competitive room level accuracy by exploiting user motions from mobile phones without site survey and low human cost without time consuming.

Usually, there are significant differences between the measured signals during the online phase and the ones on the offline phase using RM. The difference comes from several reasons. For instance, the mobile type, which is used for surveying the environment, may have different properties from the one that is used during the online phase. Hence, the location estimation error

may increase. (Mestre, P., et al., 2013) proposed a technique in order to reduce the location estimation error without any calibration procedure.

In UnLoc approach (Wang, H., et al., 2012) the mobile device sensor that senses the landmarks can recalibrate their location, for this reason no need for offline phase in this approach.

ARIEL (Jiang, Y., et al., 2012) presents a technique to automatically detect the room fingerprints based on Wi-Fi signature. Moreover this technique provides accuracy of 95%.

Peer assisted localization approach (Liu, H., et al., 2014) has studied indoor localization issues based on proposing Smartphone based techniques, this approach conducted an empirical investigation of the suitability of Wi-Fi localization, in order to get highly accurate indoor localization of Smartphone.

LiFS has proposed an indoor localization system based on off the shelf Wi-Fi infrastructure and Smartphones by (Yang, Z., et al., 2012). Regarding to calibration process of fingerprints in LiFS is crowd sourced and automatic, thus a little human intervention is needed.

“Hybrid Technique for Indoor Positioning System based on Wi-Fi Received Signal Strength Indication” has proposed by (Torteeka, P., et al., 2014), combines the advantages of both systems, trilateration and fingerprinting, which is able to improve the robustness and the accuracy stability by achieved a certain level of positioning system accuracy.

The proposed approach has enhanced the conventional fingerprinting technique by using a unique signature for each section (Room or Corridor) inside a building, it consist of the results of processing RSS, acceleration and direction readings from APs, accelerometer sensor and orientation sensor respectively. The proposed approach composed of two main phases, the offline phase and the online phase. The result of offline phase stored in the database as a signature for each section called offline signature. While the result of online phase called online signature. The online signature will be compared with the offline signatures, then the user’s position is determined by a new algorithm proposed in our study called lookup algorithm.

2. 3 Limitations Of Indoor Positioning System Techniques

In this section, we give a succinct summary of limitation the current state of art for the most popular indoor positioning techniques, which are triangulation, trilateration and fingerprinting.

2.3. 1 Triangulation

Indoor positioning techniques that have high robustness can function well even in the absence of some signals or in cases where some RSS value and angle character appear for the first time. There are cases where a signal is blocked totally from the transmitter unit; thus, the signal fails to reach the destination and cause problems with accuracy as the data obtained from other measuring units may not be accurate (Chang, N.,et al., 2010).

In terms of cost is a combination of many factors that are, time, cost, energy, and space. Regarding to cost, every base station needs to have an equipment upgrade and needs large and complex hardware requirements (Al Nuaimi, K., et al., 2011). If the Smartphone target moves farther from the measuring units, the location estimate will expose to degradation. In addition, the angle measurements need to be accurate to acquire good accuracy for positioning (Liu, H., et al., 2007).

Table (2.1) shows the summary of comparison between some existing works that are uses triangulation technique to determine the position.

Table 2.1: Summary of comparison between IRIS LPS and Active Bat (Gu, Y., et al., 2009)

System name	**IRIS LPS** (E. Aitenbichler, et al. 2003)	**Active Bat** (Woodman, O. J., et al. 2010)
Cost	Moderate	Expensive
Performance	Error range is about 16 cm.	The accuracy is about 3.0 cm with 95% probability.
Robustness	IRIS LPS can only locate a static object with acceptable accuracy For moving objects, the system need to be improved.	Influenced by reflection and obstacles between a tag and a receiver.
Complexity	Low.	Lots of receivers need to be mounted on the ceiling.
Limitation	A trade-off between accuracy and coverage.	Deploying large mounted on the ceiling numbers of sensors on the ceiling for each room is a time consuming task.

From Table (2.1) we can conclude that the triangulation technique requires more complex hardware and software, which are increasing the cost of the system. For example, it requires directive antennas, and trigonometric equations which are more complex than trilateration technique equations (Sanchez, A., et al., 2009).

2.3. 2 Trilateration

In this technique, measurements are always made in consideration of at least three points of reference. This might be a challenge when there are less than three points of references to be considered. Two limitations come because of this technique. The first limitation, is that all the receivers and the transmitters in the application must be synchronized precisely. Another significant one is that time-stamp, is required and is labeled to the sending signal to allow the measuring device to determine the distance traveled by the signal. The distance is measured using signaling techniques like Ultra Wide Band (UWB) and direct sequence spread-spectrum (Al Nuaimi, K., et al., 2011).

Signal attenuation-based, is a challenge to Line Of Sight (LOS) channel existing between the receiver and the sender. In the case of radio propagation located in such an environment, it would have difficulties with multipath effect. This means that the angle and time taken for a signal to arrive would be altered with by multipath effect leading to decreased in the accuracy of the estimated location (Al Nuaimi, K., et al., 2011). This limitation can be reduced with an alternative technique to overcome the attenuation of the signal strength. Another challenge for the measuring unit is a determination of the exact processing time or delay that is caused by the responder in this method. In medium and long ranges, the delay posed by the responder could be more, and this would cause issues with accuracy (Gu, Y., et al., 2009).

2.3. 3 Fingerprinting

The significant problems of the fingerprinting technique arise due to RSS limitations such as, signal attenuation and scattering. One of these problems is calibration problem, which means when any changes occur in indoor environment such as installing or removing a new AP and rearranging the furniture design, we must re-surveying the building regularly to overcome the RSS limitations. The need to re-surveying the building is to rebuild the RM during the offline phase, thus the overhead which is participated in the searching process presents a big challenge. So the processing overhead which is required to build the large RM database is considered another problem. In

order to reduce the overhead and to obtain an accurate position, complex search algorithms have been used, also this poses a new challenge (Le Dortz, N., et al., 2012), (Liu, H., et al., 2007).

Some existing approaches which use the fingerprinting technique to locate the user have many limitations, the proposed work from (Liu, H., et al., 2014) does not pose much more latency than required in the indoor localization and has negligible impact on the battery lifetime, however it reduce the maximum and 80% errors to as small as ranging between 1-2 m, in a time no longer than the original Wi-Fi scanning. LiFS has many radio-based solutions requires no site survey and no specific infrastructure, but the average localization error of LiFS is 5.88 m larger than the state-of-the-art model-based approaches with room error rate exceeds 10% (Yang, Z., et al., 2012).

The proposed work by (Torteeka, P., et al., 2014) consists of two techniques, trilateration is the first technique and its very sensitive to noise effect, while the fingerprinting is the second technique, the accuracy of this technique depends on training data set and it does not work well when environment changes, but it can achieve a certain level of positioning system accuracy. The ARIEL system still needs much effort to build the database; however it can detect the user’s position in room level accuracy up to 95% (Jiang, Y., et al., 2012).

2. 4 Summary

In synopsis, the current indoor localization techniques suffer from multiple drawbacks. Fingerprinting technique needs to rebuild the enormous radio map database occasionally because of signal attenuation, which needs a considerable measure of effort, this so-called calibration. Trilateration technique faces some shortcomings of wrong distance estimation because of multipath. Triangulation technique requires more complex hardware and software, which are increasing the cost of the system. The proposed approach addresses these drawbacks in various ways. To begin with, examining the RSS of APs gives various marks in comparing to the areas in indoor environments, which can be utilized to give an accurate user's position in competitive accuracy depending only on the RSS. Second, a signature which is built for each section inside the building that stored in the database is utilized to construct the signature map rather than only RSS, in order to reduce the calibration. Third, the proposed approach can determine the user's location using only the values of user's direction with dispensing the RSS in case the Wi-Fi service lost indoor with a good accuracy.

Chapter Three: Proposed Approach

3.1 Overview

The aim of this chapter is to examine how to accurately determine the user's position inside indoor environment depending on Wi-Fi technology and Smartphone sensors. We proposed a new approach for localization based on fingerprinting technology. In this approach, we address the limitations of the conventional fingerprinting technique such as the effort of building the RM, the size of database, the energy consumption and the calibration. So, there is no need for complex search algorithm.

The rationale base behind our approach is that most of the people have the consistent movement patterns when they enter the building sections (e.g. rooms and corridors). Based on this observation, the direction of the user can be used as a part of the localization signature. All the Smart phones have a sensor called orientation sensor in which the direction can be derived. The consistency of user's walking during their daily life is a significant factor that can be used in detecting the user's position. For instance, the walk speed in corridors is different from rooms. Each room has its own walking signature due to the difference in furniture and design. Therefore, the walking direction is different from room to room, even the adjacent rooms which have the similar design and furniture since the orientation sensor gets affected by the magnetic fields and the readings of RSS vary between the adjacent rooms, therefore, the adjacent rooms may have different signature.

The proposed approach uses Smartphone's sensors to measure the person direction and acceleration, and uses the existing wireless infrastructure to collect RSS readings, so there is no need for an extra hardware. It consists of two main phases, the offline phase and the online phase. During the offline phase, some steps are conducted. First, each section of the building is surveyed more than one time in order to determine a unique signature for each section. Second, the acceleration data is collected from the 3-axis accelerometer sensor in order to detect the user's movement status depending on a dynamic threshold (Chon, Y., et al., 2011). Third, the RSS values are collected from the public Access Points (APs) in the building. The average of RSS values from each AP will be computed in order to reduce the effects of the signal's attenuation and it can be used to lead to the nearest AP. Fourth, the user's direction is determined by recording the readings of the orientation sensor inside each section of the building. Lastly, the result of offline phase is stored in the database as a signature for each section called offline signature.

During the online phase, the measured real time acceleration, RSS, and user's direction form the online signature. Online signature will be compared with the offline signatures, then the user's location is determined by using lookup algorithm.

3.2 Assumptions

The proposed approach depends on the following assumptions: First, each building is covered by a number of APs. These APs share the same SSID (Service Set IDentifier) and are distributed based on well topological form inside the building. Second, the MAC address of each AP is stored in the database in advance in order to exclude the private APs. Third, the user should hold the Smartphone in his/her hand in order to detect his/her position.

3.3 System Architecture

The architecture of our system follows the diagram illustrated in Figure (3.1). The data is measured in two phases, offline phase where the data is collected, and the online phase where the user's position is detected. In the offline phase, the readings from orientation and accelerometer sensors, in addition the RSS values from all APs for each time window (e.g. 2 second) are collected. The result of the offline phase is the offline signature which can be represented as a vector of <A, R, D> where A is acceleration threshold, R is the average of the RSS values, and D is a vector of all the possible directions inside the building section. The signatures of all sections will be stored in a database called signature map. The online phase estimates the user's location by comparing the online signature which is formed when a user asks for his/her location, with the offline signatures using the lookup algorithm.

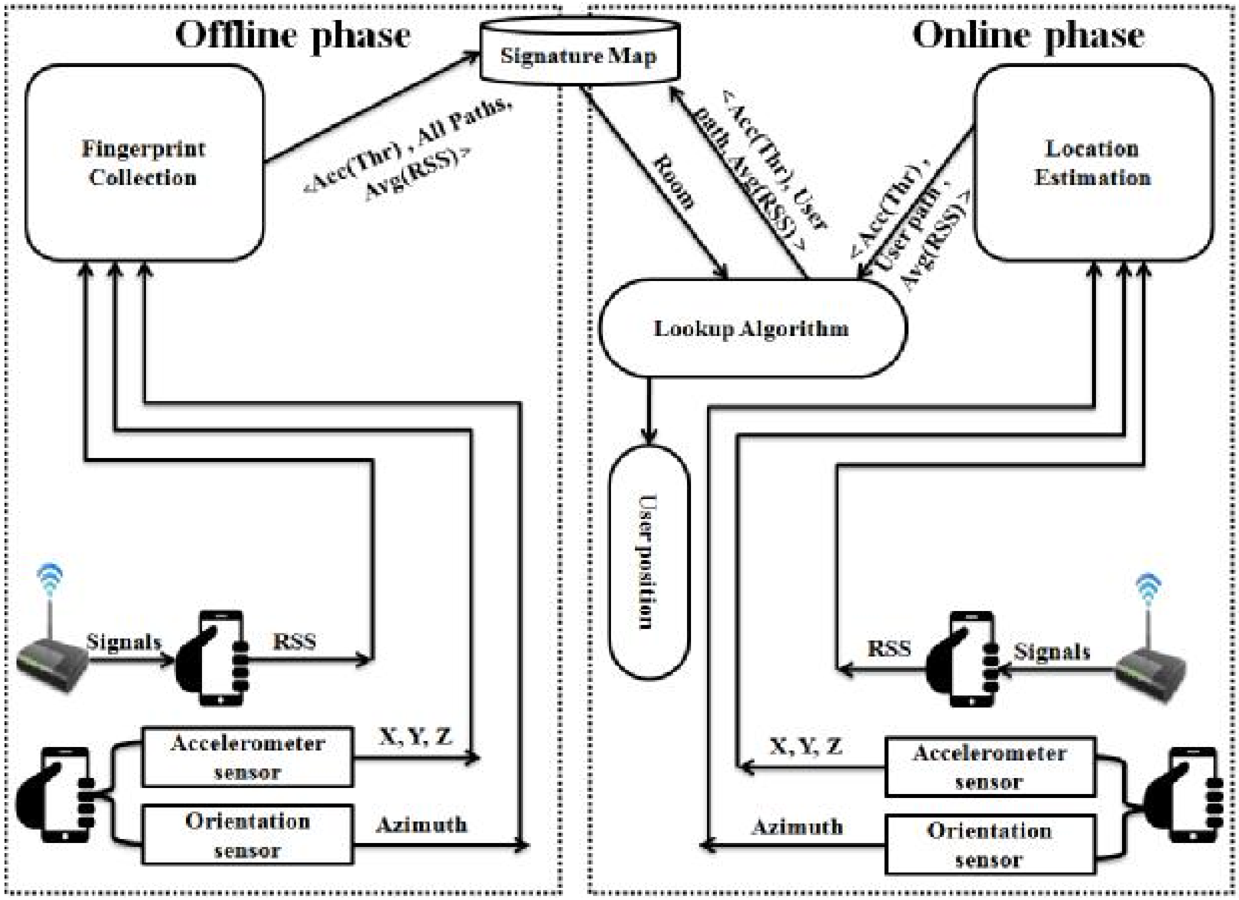


Figure 3.1: Block diagram for the proposed approach

3.3.1 Offline Phase

In this phase, the azimuth values from orientation sensor and the RSS values from APs are used as the basis for positioning, as well as, the acceleration readings from accelerometer sensor determine whether the user is stationary or moving. The Azimuth value gets affected by the phone vibrations depending on the movement of the user at four directions (North, East, South and West). RSS values get affected by any change in the environments such as passing people, changing the furniture, or adding/removing an AP.

The next subsections will illustrate the method of constructing the data base based on acceleration, RSS, and direction readings

I. Detecting The Acceleration

The accelerometer sensor measures or senses the forces of acceleration that may arise due to gravity of tilting or movement action.

The Smartphone accelerometer is a digital accelerometer that measures the acceleration. The measured acceleration includes the gravity and the physical acceleration (change of velocity). Figure (3.2) shows the forces that the accelerometer sensor measures on the x, y and z axes (Woodman, O., et al., 2007).The acceleration on (x, y) axes represents the change due to rotating or tilting the Smartphone, while the acceleration on z-axis represents the change due to vertical movements (Motion sensor., 2016).

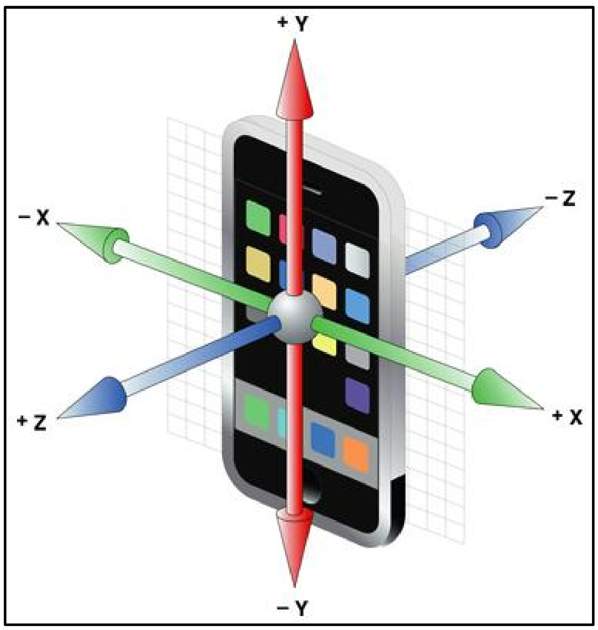


Figure 3.2: 3-axis accelerometer

One of the most important uses for the accelerometer sensor is detecting the motion. The measured acceleration on three axes can be used to determine the user's movement status whether is moving or stationary.

Life map detects the motion status of the user based on the 3-axis accelerometer readings, and a predefined threshold value (Chon, Y., et al., 2011). The proposed approach uses the Life map technique with slight modification as follows: First, the readings of 3-axis accelerometer are collected for a window of time (e.g. 5 second) in both cases whether stationary or moving inside each section of the building. Second, the magnitude for each reading is calculated using Equation (3.1), then the average of magnitude for

all values is computed. Third, the average of magnitude is subtracted from magnitude value for each reading, in order to exclude the gravity force. Finally, the Standard Deviation (St. D) is computed.

Magnitude(x, y, z) = $\sqrt{\mathbf{X^2 + Y^2 + Z^2}}$ **Equation (3.1)**

Where,

X is: Acceleration force along the x axis (including gravity) m/s^2.

Y is: Acceleration force along the y axis (including gravity) m/s^2.

Z is: Acceleration force along the z axis (including gravity) m/s^2.

The acceleration threshold value is selected depending on the standard deviation value, which is calculated for each section in the building, in both users' movement status, stationary or moving. Table (3.1) illustrates an example of computing the threshold. The data in the table has been taken from real experiments are conducted in IT department at Mu'tah university for eleven sections.

Table 3.1: An example of computing a threshold (Offline phase)

	Standard Deviation (StD)	
IT department	**Stationary**	**Moving**
Room 1	0.06	1.18
Room 2	0.03	**0.82**
Room 3	0.03	1.24
Room 4	**0.10**	1.13
Room 5	0.07	1.50
Room 6	0.04	1.04
Room 7	0.07	0.92
Room 8	0.05	0.91
Room 9	0.08	1.17
Corridor 1	0.07	1.40
Corridor 2	0.03	1.60

According to Table (3.1), the maximum value of St. D when the user is stationary is 0.10, while the minimum value of St. D is 0.82 when the user is moving. Therefore, the acceleration threshold will be the average of the maximum value of St. D when the user's movement status is stationary, and the minimum value of St. D when the user's movement status is moving. This means if the St. D is greater than the empirical threshold value, the user is moving, otherwise is stationary.

II. Detecting The Received Signal Strength

In general, reliance on Wi-Fi signals for indoor localization is the most popular right now, because of its proliferation and availability in the majority of the buildings at the current time, also the lack of more efficient technologies inside the buildings for the localization. Smartphone which is equipped by Wi-Fi detector is widely spread in current time. For that, the Wi-Fi RSS which is derived from APs is used as the basis for user's positioning. So, the proposed approach is needed to retrieve RSS values from these APs in order to detect the user's position.

The collection process of RSS values consist of two stages. In the first stage, the RSS values from each AP for each section in the building are measured. Then, the average of RSS readings for each AP in each section is computed. Last, the calculated average is stored in a signature map as one part of offline signature as illustrated in Table (3.2). In the second stage, the accurate user's position is determined based on predefined landmark using the computed average RSS values.

The purpose of the first stage is to select the user location depending on the room level accuracy. Then the second stage is used to compute the accurate position by computing the estimated distance between the user and a landmark.

During the first stage, the readings of RSS are collected as follows: First, the surveyor who builds the database during the offline phase surveys each section in the building, to collect the RSS values from all public APs, as well as the direction values according to the expected user's paths. Second, the average of all RSS readings in each path is computed. Third, the average of RSS in all paths is stored in the signature map as one component of offline signature. Table (3.2) shows an example of RSS data in offline signature which was collected from real experiments were conducted inside IT department building.

Table 3.2: RSS Data in offline phase - IT department

	Average value of RSS readings						
	AP5	**AP2**	**AP4**	**AP7**	**AP6**	**AP3**	**AP1**
Room1	-81	-62	-71	-83	-86	-92	-99
Room2	-84	-74	-55	-78	-89	-99	-99
Room3	-70	-59	-78	-88	-73	--80	-89
Room4	-71	-63	-75	-85	-86	-87	-86
Room5	-87	-77	-66	-73	-99	-99	-99
Room6	-80	-79	-92	-99	-69	-61	-81
Room7	-77	-89	-99	-99	-56	-78	-86
Room8	-80	-89	-99	-99	-72	-64	-79
Room9	-88	-91	-99	-99	-84	-68	-68
Corridor1	-65	-59	-51	-59	-84	-88	-99
Corridor2	-59	-83	-87	-83	-57	-53	-63

Table (3.2) presents the average values of RSS readings from all public APs for each section. The public APs which were distributed inside IT department during conducting a real experiments are APs (1, 2, 3, 4, 5, 6, and 7).

Table 3.3: Average of RSS readings in Room3 (Offline phase)

	AP5	**AP2**	**AP4**	**AP7**	**AP6**	**AP3**	**AP1**
Path1	-74	-50	-77	-91	-78	-81	-90
Path2	-69	-67	-86	-88	-70	-79	-87
Path3	-68	-60	-72	-86	-72	-80	-90

Table (3.3) illustrates an example of computing the average of RSS values in room 3 at the IT department building, which has three paths, which the user can choose one of them to enter to the room. The values in the table represent the average value for each path.

During the second stage, three steps are performed. First, the surveyor determines landmark in each section inside the building. Second, The RSS readings on a landmark inside each section are collected for a time window (e.g., 2 seconds). Third, the average of RSS values will be computed, then stored in the database. The stored average values will be used to compute the estimated distance on real time between the user and the landmark using Equation (3.2) (Sen, S., et al., 2013), (Peter, H., et al., 2000).

Estimated Distance = $10^{((RSS_Offline) - (RSS_Online))/(20)}$ **Equation (3.2)**
where,
RSS_Offline : Average of RSS readings in offline phase.
RSS_Online : Average of RSS readings in online phase.

The positioning technique is mainly based on the RSS especially on the fingerprinting method. The main challenge in RSS is that, it is highly responsive to the environmental changes. RSS is not always accurate because it can be affected by many factors such as walls, furniture in the building, people moving inside the building, etc. Therefore, depending on the RSS alone to detect the user's location may cause errors in position detecting and it may take a lot of time in search process. To mitigate the impact of these errors in the proposed approach, the average of RSS readings is calculated just from public APs, to make the RSS more smoothly, and in order to reduce its vulnerability to environmental changes. Also, we can benefit from orientation sensor to solve some problem that faced the RSS, such as calibration process, complex search algorithm which used to determine the user's location, and time that spend in search process.

III. Detecting The Direction

The orientation sensor is a position sensor (software-based). Also, it used to determine a device's position. According to assumption 3 in Section (3.2) we can conclude that, as long as the user holds the Smartphone in his/her hand, the orientation sensor can be used to determine user's direction. We can benefit from orientation with the RSS in order to make the positioning more accurate and to minimize the database size (this shown by limiting the search and comparison processes that used to determine the user's location) (Position sensor, 2016). Position sensors are not typically used to monitor device movement or motion, such as shake, tilt, or thrust. It just used to determine the position of a device or user's position depending on some assumptions. Moreover, the orientation sensor derives its data by using a device's geomagnetic field sensor in combination with a device's accelerometer. Using these two hardware sensors, an orientation sensor provides data for the following three dimensions (Position sensor, 2016):

- Azimuth (degrees of rotation around the z axis). This is the angle between magnetic north and the device's y axis.

- Pitch (degrees of rotation around the x axis). This value is positive when the positive z axis rotates toward the positive y axis, and it is negative when the positive z axis rotates toward the negative y axis.

- Roll (degrees of rotation around the y axis). This value is positive when the positive z axis rotates toward the positive x axis, and it is negative when the positive z axis rotates toward the negative x axis (Position sensor, 2016).

In our proposed work the azimuth value is used in order to determine the user's direction, depending on the direction of Smartphone that holds in user's hand.

Table 3.4: Conversion between azimuths and compass points (Han. S, et al. 2012).

Azimuth	Direction	Azimuth	Direction
0° - 22°, 338° - 360°	**N**	**158° - 202°**	**S**
23° - 67°	**NE**	**203° - 247°**	**SW**
68° - 112°	**E**	**248° - 292°**	**W**
113° - 157°	**SE**	**293° - 337°**	**NW**

Azimuth value is the most important value, since it can be used to determine the direction; each range of angles represents a direction as shown in Table (3.4) (Han, S., et al., 2012).

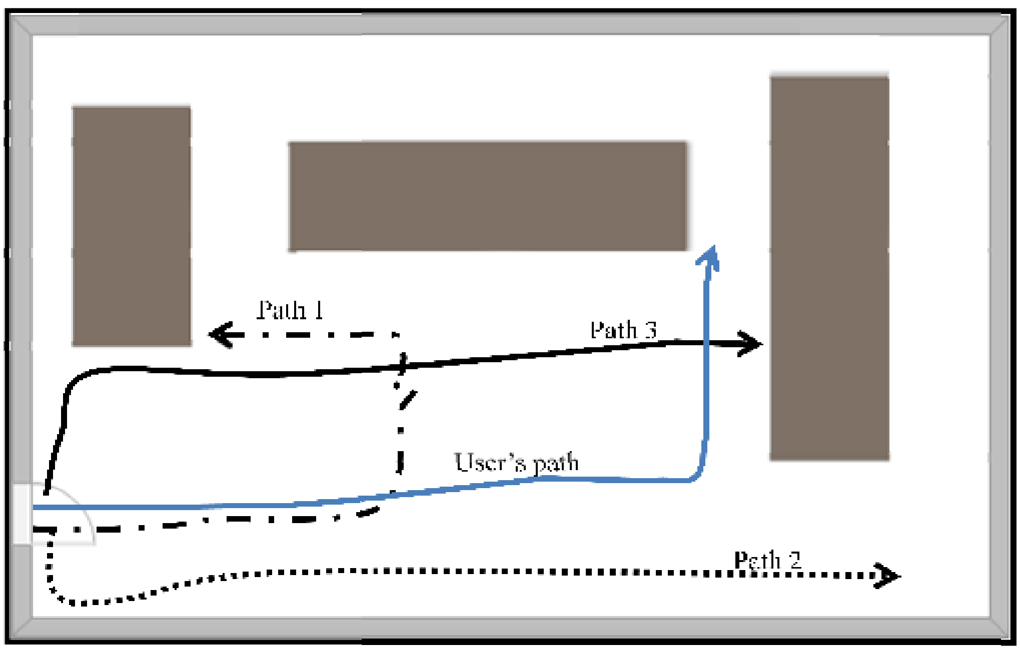


Figure 3.3: The results of monitoring the user's paths into the room

As illustrated in Figure (3.3), path 1, path 2 and path 3 are the expectedly ways that a user can use when he/she enters a room. Each way has a unique

user's movement pattern in terms of direction. The proposed approach utilizes this observation to recognize the user's position. To do so, the following table should been filled as shown.

Table 3.5: Direction values for 3 paths inside a room

Path	Path 1					Path 2			Path 3		User's path	
Direction No.	236 E	7 N	5 E	57 N	148 E	5 W	61 S	415 E	59 N	541 E	270 E	304 N

Table (3.5) presents the number of direction values for all paths that are shown in Figure (3.3). Where E indicates to East direction, W to West, S to South, and N to North.

Detecting the direction process in the proposed approach is performed by following steps: First, monitor the movement pattern of people who entering into the sections inside the building, in order to find out all the expected paths that maybe used by the users to enter a section during their daily life. Second, the surveyor surveys each section inside the building more than once according to expected paths that have been extracted, e.g. Section 1 à (path 1, path 2,..., and path n), where n represents number of expected paths. Third, the azimuth values for each path inside the section are converted to a real direction according to Table (3.4). Fourth, the result of conversion is stored in the database. The purpose of storing the values of direction is to compute the similarity ratio between the online path and the stored paths.

Table 3.6: Conversion from azimuth values to directions values_IT department (Offline phase).

Room1_Azimuth			**Room1_Direction**		
Path1	**Path2**	**Path3**	**Path1**	**Path2**	**Path3**
323.1973	276.50714	277.18646	NW	W	W
323.60464	276.68213	277.25992	NW	W	W
323.95578	276.86652	277.39966	NW	W	W
324.31082	277.04868	277.5323	NW	W	W
324.60223	277.256	277.68954	NW	W	W
324.8171	277.45386	277.8827	NW	W	W
324.96942	277.67645	278.0752	NW	W	W
325.10928	277.86966	278.23993	NW	W	W
325.27594	278.04004	278.38577	NW	W	W
325.45795	278.15668	278.5288	NW	W	W

Table (3.6) shows an example of converting the azimuth values according to Table (3.4) to real direction, where the W means West and NW means North West.

IV. **Fingerprint collection**

The Result from offline phase in our approach called fingerprint collection. The final outputs of processing the RSS values from APs, and the readings of 3-axis accelerometer and orientation sensors, are stored in signature map as a unique signature called offline signature. The offline signature is formed for each section which is surveyed inside the building as a vector < A, R, D> as shown in Table (3.7). The purpose of storing these signatures is to detect the user's location when compare the online signature with the offline signatures.

Table 3.7: Offline phase data for IT department

Sensor readings			Average of RSS readings from all APs						
	Thr(Acc)	**No of Paths**	**AP1**	**AP3**	**AP6**	**AP7**	**AP4**	**AP2**	**AP5**
Room1	0.46	3 paths	-99	-92	-86	-83	-71	-62	-81
Room2	0.46	2 paths	-99	-99	-90	-78	-55	-74	-84
Room3	0.46	3 paths	-89	-80	-73	-88	-78	-59	-70
Room4	0.46	2 paths	-86	-87	-86	-85	-75	-63	-71
Room5	0.46	2 paths	-99	-99	-99	-73	-66	-77	-87
Room6	0.46	2 paths	-81	-61	-69	-99	-92	-79	-80
Room7	0.46	2 paths	-86	-78	-56	-99	-99	-89	-77
Room8	0.46	2 paths	-79	-64	-72	-99	-99	-89	-80
Room9	0.46	2 paths	-68	-68	-84	-99	-99	-91	-88
Corridor1	0.46	2 paths	-99	-88	-848	-59	-51	-59	-65
Corridor2	0.46	2 paths	-63	-53	-57	-83	-87	-83	-59

The Thr (Acc) in Table (3.7) means that the acceleration threshold which is computed from the readings of 3-axis accelerometer sensor as presented in Table (3.1). As for the No of paths that stored in the table, it reflects the number of paths that tracked by the surveyor inside each section of the building.

3.3.2 Online Phase

The online phase needs to collect data on real time to construct the online signature, and then compare it with those in the database (signature map) which are called offline signatures. To do so, the techniques of gathering the

data such as RSS, acceleration, and azimuth, from APs, accelerometer sensor, and orientation sensor respectively are the same techniques that have been used during the offline phase. A new proposed algorithm called lookup algorithm takes the responsibility of matching the online signature with the offline signatures.

The following subsections provide the details about each part of the online phase, which includes detecting the acceleration, detecting the RSS, detecting the direction, location estimation and lookup algorithm.

I. Detecting The Acceleration

According to the user's path a number of steps are conducted to detect whether the user is stationary or moving. First, the acceleration readings from 3-axis accelerometer sensor are collected. Second, the St. D is computed as mentioned in offline phase part. Third, the St. D is compared with the acceleration threshold value which has been computed during the offline phase, in order to identify the user's movement status.

Table 3.8: An example of computing a standard deviation (online phase- IT department)

IT department	Standard Deviation(St. D)
Section 1	**0.14**
Section 2	**0.12**
Section 3	1.16
Section 4	**0.08**
Section 5	1.50
Section 6	1.02
Section 7	0.98

Table (3.8) shows the St. D values for some sections at the department of IT. The St. D value for these sections 1, 2, and 4 are approximately equal to 0.14, 0.12 and 0.08 respectively which are less than the value of the acceleration threshold in IT department (0.46). Therefore, the system decides that the user is stationary in these sections. In contrast, the St. D values for sections 3, 5, 6, and 7 are approximately equal to 1.16, 1.50, 1.02 and 0.98 respectively which are greater than the value of the acceleration threshold. Therefore, the system decides that the user status is moving.

Look up algorithm needs the user's movement status in order to determine the best way of locating the users.

II. Detecting The Received Signal Strength

RSS values will be used in two stages. During the first stage, it will be used to detect the user in room level accuracy. While, during the second stage, the position of the user will be detected in the sections.

In the first stage, during the movement of the user inside the building, the RSS values are gathered inside each section according to user's path, then the average of RSS values0 are computed. Table (3.9) shows an example of the RSS average for all the available APs in each section at IT department.

Table 3.9: RSS Data in online phase - IT department

	Average value of RSS readings						
	AP5	**AP2**	**AP4**	**AP7**	**AP6**	**AP3**	**AP1**
Section1	-84	-64	-67	-86	-83	-90	-99
Section2	-84	-76	-56	-79	-90	-99	-99
Section3	-70	-59	-75	-86	-68	-79	-90
Section4	-70	-61	-73	-87	-87	-88	-92
Section5	-87	-80	-59	-72	-99	-99	-99
Section6	-78	-79	-88	-99	-69	-59	-80
Section7	-73	-87	-99	-99	-58	-76	-88
Section8	-86	-90	-99	-99	-75	-61	-82
Section9	-90	-89	-99	-99	-83	-74	-68
Section10	-63	-58	-54	-64	-83	-87	-99
Section12	-61	-84	-88	-91	-58	-57	-61

The value of average RSS from online signature then compared with the values of average RSS from offline signatures in order to choose the better choice using the K-Nearest Neighbour (KNN) algorithm which is reflect the user's position in room level accuracy, but this accuracy is not sufficient in indoor positioning.

In the second stage, in order to acquire an accurate user's position, the Equation (3.2) is used to compute the estimated distance on real time between the user and the landmark, after detect the user's position in room level accuracy, the average RSS is determined by Smartphone of the user who wants to locate his/her position, then the accuracy in meter is given, thus the accuracy of our proposed approach will be sufficient in indoor positioning.

III. Detecting The Direction

The process of collecting and processing the azimuth value in online phase is accomplished as presented in offline phase. During collecting and processing the data that collected from orientation sensor, three steps are performed. In the first step, the azimuth values are collected according to the user's path. In the second step, the azimuth values are converted to directions depending on Table (3.4). Finally, the conversion results are stored in online database as shown in Table (3.10).

Table 3.10. Conversion from azimuth values to directions values (Online phase).

Room1_User's path – IT department			
Azimuth	**Direction**	**Azimuth**	**Direction**
267.9757	W	269.60385	W
268.39853	W	269.74963	W
268.8059	W	269.8722	W
269.15332	W	269.97986	W
269.417	W	270.09933	W

IV. Location Estimation

The main purpose of the data collection process in the online phase is to determine the user's location. In order to do that, the online signature is formed, and then it will be used by the lookup algorithm in order to locate the user.

Table 3.11: Online phase data for IT department

Sensor readings			**RSS from all APs**						
	St. D(Acc)	**User's Paths**	**AP1**	**AP3**	**AP6**	**AP7**	**AP4**	**AP2**	**AP5**
Section 1	0.14	The result of conversion the azimuth values for a user's path	**-99**	-90	-83	-86	-67	-64	-84
Section2	0.12		**-99**	**-99**	-90	-79	-56	-76	-84
Section 3	1.16		-90	-79	-68	-86	-75	-59	-70
Section 4	0.08		-92	-88	-87	-87	-73	-61	-70
Section 5	1.50		**-99**	**-99**	**-99**	-72	-59	-80	-87
Section 6	1.02		-80	-59	-69	**-99**	-88	-79	-78
Section 7	0.98		-88	-76	-58	**-99**	**-99**	-87	-73
Section 8	0.051		-82	-61	-75	**-99**	**-99**	-90	-86
Section 9	1.18		-68	-74	-83	**-99**	**-99**	-89	-90
Section10	0.95		-99	-87	-83	-64	-54	-58	-63
Section11	0.05		-61	-57	-58	-91	-88	-84	-61

Table (3.11) shows an example of the online signature for each section at IT department. The signature will be sent to the signature map by lookup algorithm as unknown section. Then, I compared it with all offline signatures in order to determine the user's position.

V. Lookup Algorithm

The previous sections show how the data is gathered in order to create a unique signature for each section in the building. In this section, a new searching algorithm called lookup algorithm is proposed. It takes the measured data from online phase which is called online signature, and looks for the offline signatures that are stored in a signature map, in order to get the most appropriate signature that may lead to the real user's position.

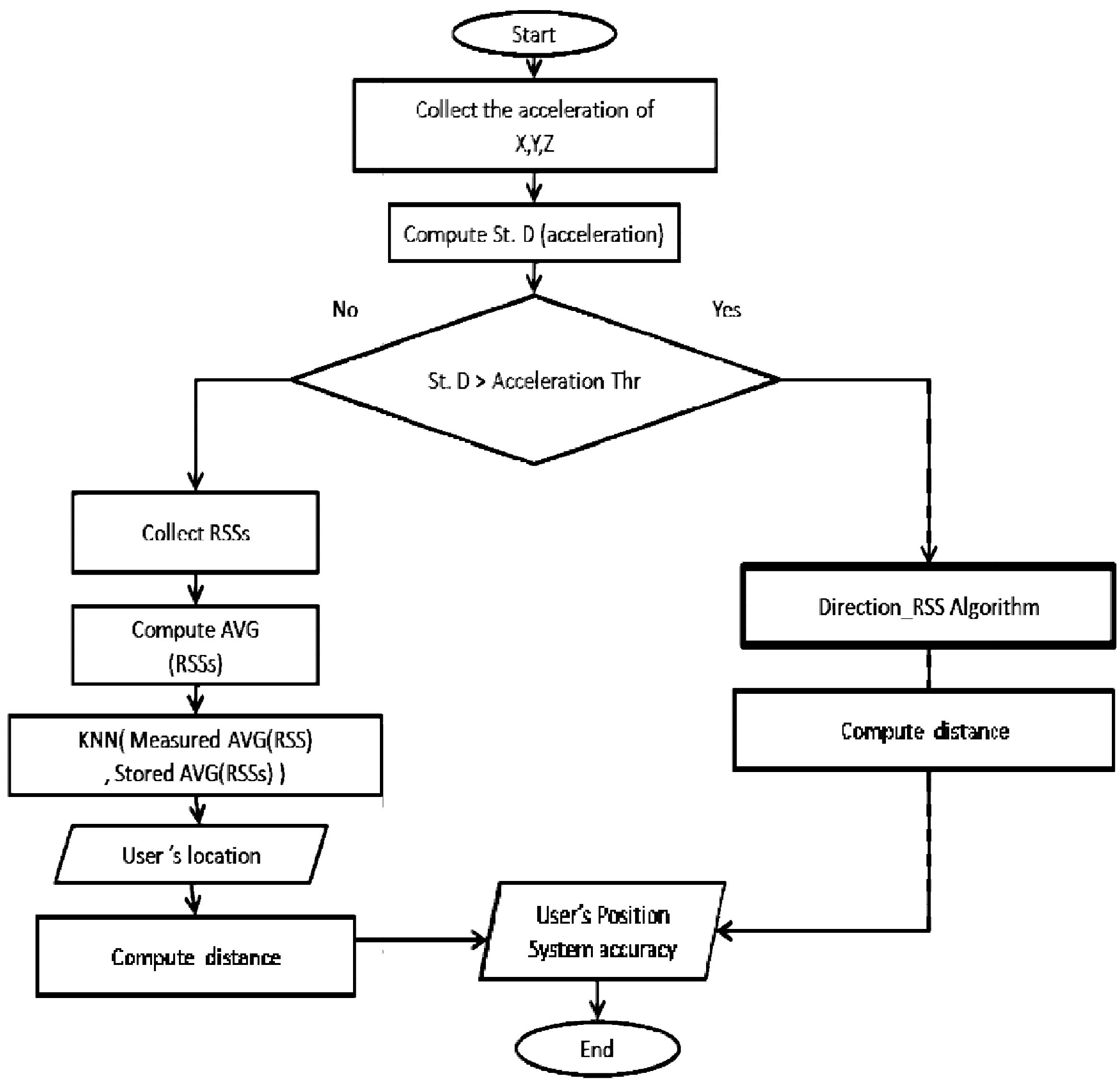


Figure 3.4: Locating user position algorithm flowchart

The proposed algorithm has two phases: in the first phase, the position of the user will be determined in room level accuracy, while in the second phase the distance between the user and a landmark in the selected section (room or corridor) will be computed in order to detect the position of the user in better accuracy.

User's direction will be estimated in the first phase in order to reduce the number of returned sections from the database to reduce the amount of search time, which leads to a better algorithm's complexity. Then the RSS will be used in the second phase to detect the accurate user's position.

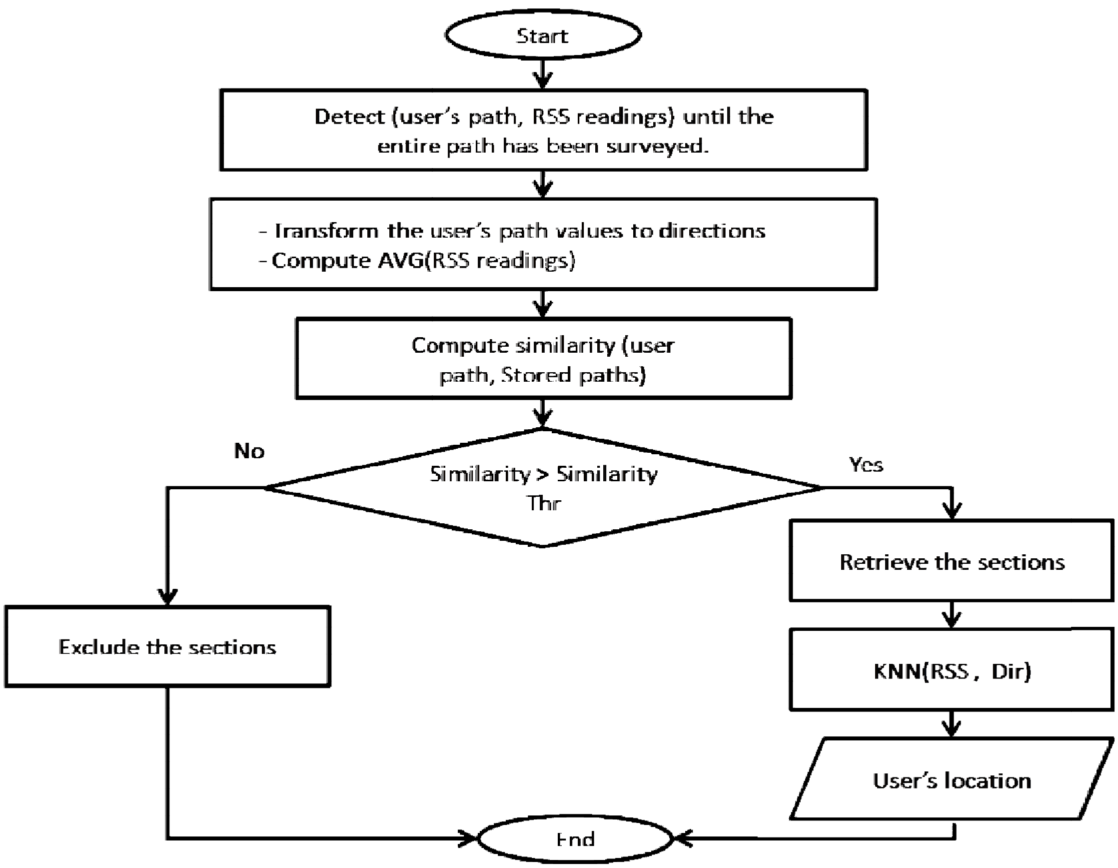


Figure 3.5: Direction_RSS algorithm flowchart

Figure (3.4) and Figure (3.5) show the lookup algorithm flowcharts, which works as follows. The algorithm detects the user's movement status according to the standard deviation of the acceleration. If the user is stationary, then the stationary part is activated, otherwise, the movement part is activated. The following is the details about each part.

Stationary part: in this part, the average RSS values will be used to detect the user's position. KNN algorithm is used to choose the best match between the measured real time RSS average values from online signature and the stored offline RSS data from offline signatures, the result will be the section that the user is located in. The estimated distance is then computed between the user and the registered landmark in the corresponding section using Equation (3.2), in order to detect the accurate user's position inside the section.

The KNN algorithm reduces the efforts of computations, improves the stabilization and localization accuracy, and is effective and robust to noisy data (Yu, F., et al., 2014). Using KNN algorithm depends on Euclidian Distance (ED) as shown on Equation (3.3). In the proposed approach, the nearest neighbour expresses user's position in room level accuracy, which refers to the section where the user located inside it.

$$\mathbf{ED} = \sqrt{(\mathbf{MRSS} - \mathbf{SRSS1})^2 + (\mathbf{MRSS} - \mathbf{SRSS2})^2 + \ldots\ldots + (\mathbf{MRSS} - \mathbf{SRSS\,n})^2} \qquad \textbf{Equation(3.3)}$$

Where,

MRSS is : Measured AVG(RSS) which is recorded in online phase.

SRSS is : Stored AVG(RSS) which is recorded in offline phase.

n: number of sections in the building.

Movement part: in this part, the direction as well as the RSS values will be used to detect the user's position. During the user's movement in their daily life, most of users follow the same movement pattern especially when they enter a room or when they walk on the corridors. Our approach takes into account this kind of observation; therefore, the direction will be stored in the database while the user is moving. Then the measured real time direction is compared with the stored ones, in order to detect the similarities between them. If the similarity surpasses an empirical threshold (Similarity Thr) value, then the area of the user will be detected. The result is a number of section that they maybe the user located in one of them. RSS average values will be used then to decide the exact section that the user is located in, as well as the distance between the user and the registered landmark in order to detect the accurate user's position is computed, in order to determine user's location in meter accuracy.

3.4 Summary

In this chapter, a new approach for indoor positioning system has been proposed. This approach depends on RSS, acceleration and direction from APs, 3-axis accelerometer sensor and orientation respectively, to extract a unique signature for each section inside a building in order to determine the user's position.

The proposed approach overcomes the limitations in the conventional fingerprinting technique. Fingerprinting technique has been used because of its good accuracy. However, the effort and the calibration process are the main limitations which need to be solved.

Direction is used to minimize the need of the calibration process while the RSS and acceleration are used to reduce the size of the database, which leads to reduce the effort and the time of the searching on the database.

Chapter Four: Evaluation and Comparison

In this chapter, we begin with an illustration of our experimental setup, including the equipments that were used in our experiments. Then we discuss the experiments' results analyzing the result and the error. Lastly, the comparison results between our approach and existing approach are presented.

4.1 Experimental Setup

The proposed approach was evaluated in two different environments at Mu'tah University: the IT department, and the unity of admission and registration building. The layouts of these two environments are shown in Figure (4.1) and (4.2) respectively.

IT Department has dimensions of 51.6m length by width of 44.4m, an area of 2291.04m^2, and includes more than 25 sections. Unity of admission and registration has three floors with dimensions of 14.4m length by width of 25.5m, an area of 367.2m^2 for each one of them, and includes more than 12 sections in each floor.

The experiments were conducted in the IT department, which have 7 APs with average distance of 7.5m between each two of them, as presented in Figure (4.1). The experiments were conducted in unity of admission and registration building, which have 5 APs distributed in two floors, as shown in Figure (4.2) with a 6.5m between each two of them.

The APs (1, 2, 3,4,6,7 and 8) are placed in IT department at the locations indicated in Figure (4.1), and the APs (1, 2, 4, 6 and 8) are placed in unity of admission and registration at the locations indicated in Figure (4.2).

The model of the APs that are used in our experiments is ZXHN H108N; this model is an Asymmetric Digital Subscriber Line (ADSL) access device that supports multiple line modes for Bridge Head Server (BHS). Each AP supports ADSL2/ADSL2+ and is backward compatible to ADSL, it supports a wide input voltage range, which can reach 100V-240V. According to the settings on the central office Digital Subscriber Line Access Multiplexer (DSLAM) the AP provides auto negotiation capability for different standards.
This AP has good features, it provides broadband connection to the Internet by using high-speed ADSL connection, and provides secure wireless encryption modes and firewall to protect network security (Shenzhen, P., 2012).

All experiments were conducted using an Android-based Galaxy SIII Smartphone, which is equipped with orientation and accelerometer sensors, and Wi-Fi. These experiments were conducted during the daytime when may be the RSS affected by obstacles, such as pedestrian between the user's Smartphone that is used to collect the RSS readings from the public APs. Each of the APs and the Smartphone support IEEE 802.11 b/g/n Wi-Fi interfaces.

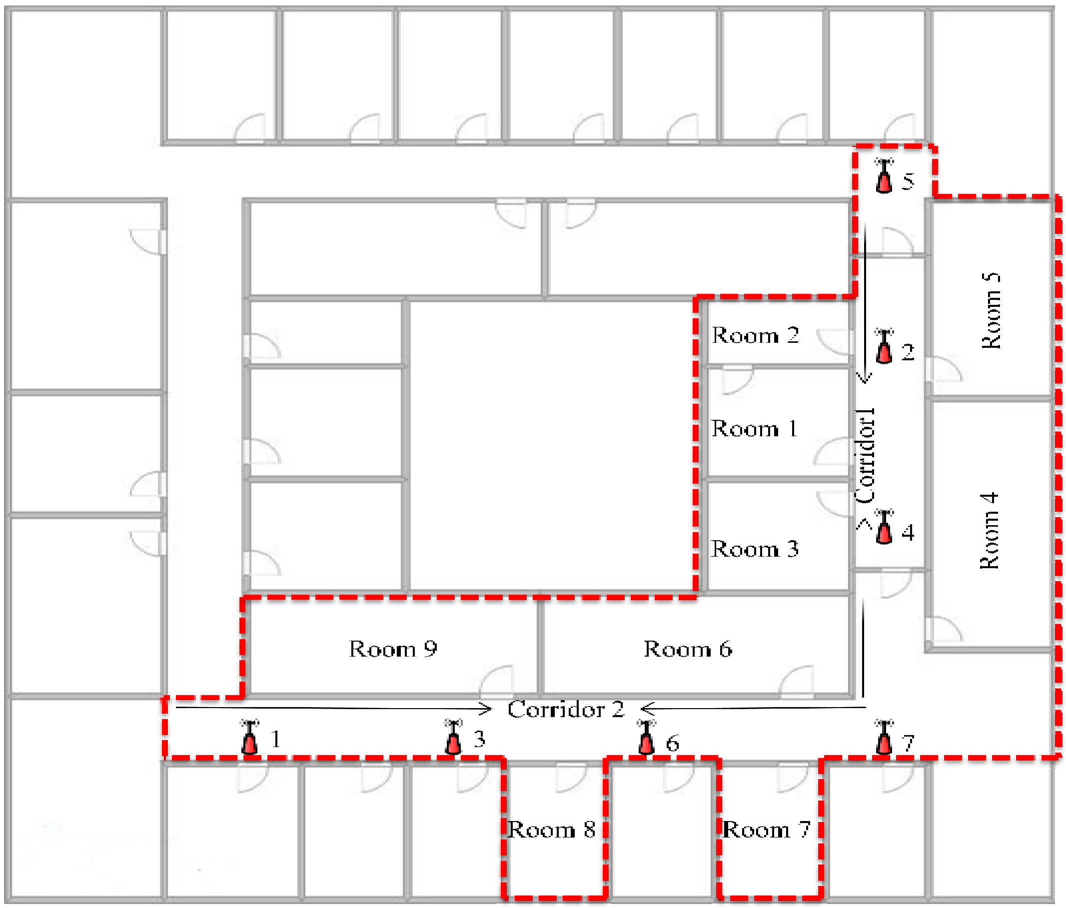
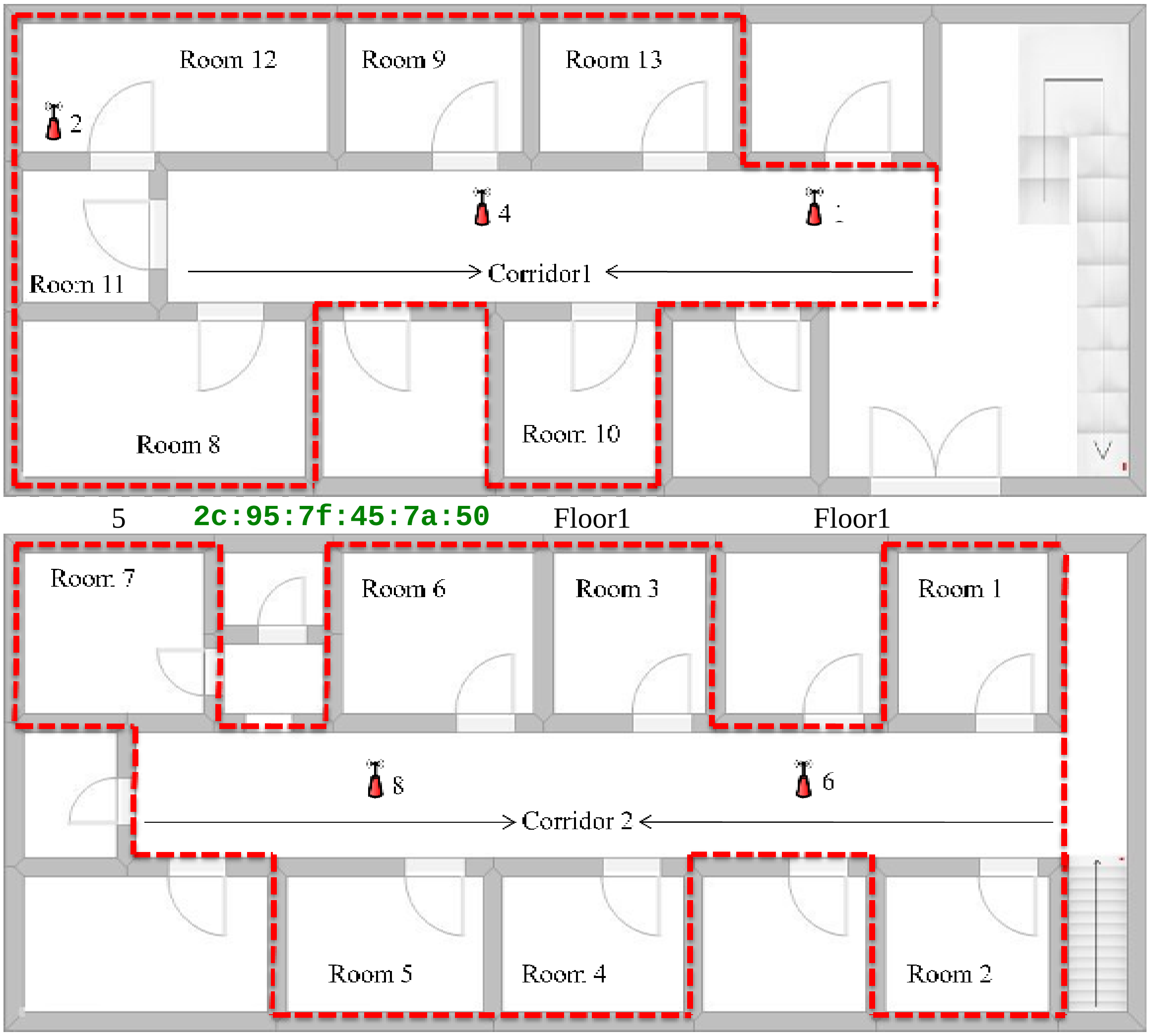


Figure 4.1: Blueprint of IT department.

 **:** Indicate to the AP

The real experiments were carried out in IT department of a typical office rooms, lecture rooms, computer labs and corridors. As shown in Figure (4.1), the IT department contains more than 25 sections which consist of rooms and corridors. The interested area which is used in the experiments is surrounded by dashed line in Figure (4.1) where eleven sections are included, of which four office rooms (Room 1,2,7and 8), four computer labs (Room 4,5,6, and 9), one lecture room (Room3), and two corridors. Totally there were seven APs are distributed inside the IT department as shown in Figure (4.1).



(b)

Figure 4.2: Blueprint for unity of admission and registration building.
(a) Blueprint of first floor, (b) Blue print of second floor.

The real experiments in unity of admission and registration building were conducted in office rooms and corridors. As shown in Figure (4.2), it contains more than 12 sections in each floor consists of rooms and corridors, but the interested area which is used to conduct the experiments is surrounded by dashed line consists of seven sections, of which six office rooms, and one corridor in first floor. In addition, eight sections in second floor consist of seven office room and one corridor. Totally there are five APs are distributed inside the unity of admission and registration building are denoted in Figure (4.2).

The APs which are used in experiments are stored in database as shown in Table (4.1), which contains MAC address and location for each one. The purpose of storing the APs as presented in the table to exclude the readings of

RSS from private APs, and determine the floor which maybe the user is located in.

Table 4.1. APs Database

APs	MAC	IT Department	Registration
1	2c:95:7f:00:15:38	Floor1	Floor2
2	2c:95:7f:45:a1:b4	Floor1	Floor2
3	2c:95:7f:53:b7:4f	Floor1	-
4	2c:95:7f:45:8d:f4	Floor1	Floor2
5	2c:95:7f:00:2e:bc	-	-
6	2c:95:7f:45:7c:2c	Floor1	Floor1
7	2c:95:7f:45:7a:50	Floor1	-
8	2c:95:7f:45:7a:50	Floor1	Floor1

4.2 Measuring The RSS Values and The Data of Smartphone Sensors

In the proposed approach we depend on RSS values, 3-axis accelerometer sensor readings and orientation sensor readings in order to detect the users' positions. We depend on android Wi-Fi manager, android sensor manager and we used the android applications in order to collect the data from Smartphone sensors and the values of RSS. These android managers and applications are presented in this section.

4.2.1 Wi-Fi Technology and Android Managers

I. Wi-Fi Technology

Wi-Fi allows a Smartphone to connect to the Internet using Wireless Access Points (WAPs). The AP receives the signals from a Smartphone and then sends it to the Internet via a physically wired connection.

Generally, the Smartphone can use one of two methods to connect with AP. Passive scan is the first method, where the AP broadcasts regularly a special frame via the wireless medium called beacon. The data that are included in the beacon frame can be used by the Smartphone in order to connect with the Internet. Therefore, the beacon can used to associate with the AP when a Smartphone receives a beacon. Usually every 100 millisecond the AP broadcasts the beacon. After that to broadcast the beacon again the AP changes its state to sleeping mode and it wakes up every 100 millisecond (Velayos, H., et al., 2004).

The active scan is the second method, in this method the Smartphones sends a frame via the medium called probe request in order to search for the available APs, a frame called probe response sends to the Smartphone from any AP hears the probe request. After that based on the data that is available in the probe response frame, the Smartphone can associate with this AP. Each AP broadcasts a signal that can be received by the Smartphone. Then the Smartphone convert this signal to a value ranging from 0 to -100, and represents the RSS. So it can be used to determine whether the user is close to AP or not (Velayos, H., et al., 2004). Some scanning approaches use the RSS to identify the quality for the signals which are broadcasting from AP, so by using the RSS they can decide which AP is better for the connection.

II. Android Wi-Fi Manager

The (Application Programming Interfaces) APIs for all the Wi-Fi functionalities provides by Java class which is called Wi-Fi manager. Using this class the devices such as Smartphone can scan for the available WLAN networks, enable or disable the Wi-Fi adapter, associate with AP, and disconnect with AP.

. Table (4.2) presents the APIs that are provided by the ScanResult class (ScanResult, 2016). This class is responsible about searching for the available WLAN using the method which is called passive scan. Using this class the device can detect the beacons which are transmitted by any to any device which is supported by Wi-Fi services such as Smartphone.

Table 4.2: ScanResult APIs

Field	Description
BSSID	The MAC address of the access point
SSID	The name of the network
Capabilities	Describes the authentication, key management, and encryption schemes supported by the AP
Frequency	The frequency in MHZ of the connected channel with AP
Level	The RSS in dBm, also known as RSSI
Timestamp	The timestamp in microseconds

III. Android Sensor Manager

Android Sensor Manager is a class that lets to access to the Smartphone's sensors and deals with all the aspects of the available sensors in it. The Android developer can get the readings of the sensors and access to the Smartphone's sensor using a pre designated APIs. Table (4.3) presents the APIs that are provided by the Sensor Manager class (Sensor Manager, 2016).

Table 4.3: SensorManager APIs

Sensor	Description	Common Uses
TYPE_ACCELEROMETER	Measures the acceleration force in m/s^2 to a Smartphone on three axes (x, y, z)	Motion detection
TYPE_ORIENTATION	Measures degrees of rotation that a Smartphone makes around all axes (x, y, z)	Determining device position
TYPE_GYROSCOPE	Measures a Smartphone's rate of rotation in rad/s around three axes (x, y, z)	Rotation Detection
TYPE_MAGNETIC_FIELD	Measures the ambient geomagnetic field for three axes (x, y, and z) in μT.	Creating a compass

Table (4.3) shows some APIs to access the Smartphone sensors, these APIs are supported by the Android platform. The android developers can manage and control everything regarding to the sensors using these APIs, such as enabling or disabling the sensor, and getting the data of the sensors.

For example, the accelerometer sensor has three values and they are supported by the API TYPE_ACCELEROMETER (Sensor Manager, 2016), these values are in SI units (m/s2), the API supports them as an array as follows:

- Values [0]: represents the Acceleration minus Gx on the x-axis.
- Values [1]: represents the Acceleration minus Gy on the y-axis.
- Values [2]: represents the Acceleration minus Gz on the z-axis.

4.2.2 Wi-Fi Analyser Application

This Wi-Fi analyser can be used to find the best location for Wi-Fi device. The analyser has 4 separate screens: Meter, Channel, Graph and List. In real experiments were conducted in our approach we used list channel to collect RSS readings.

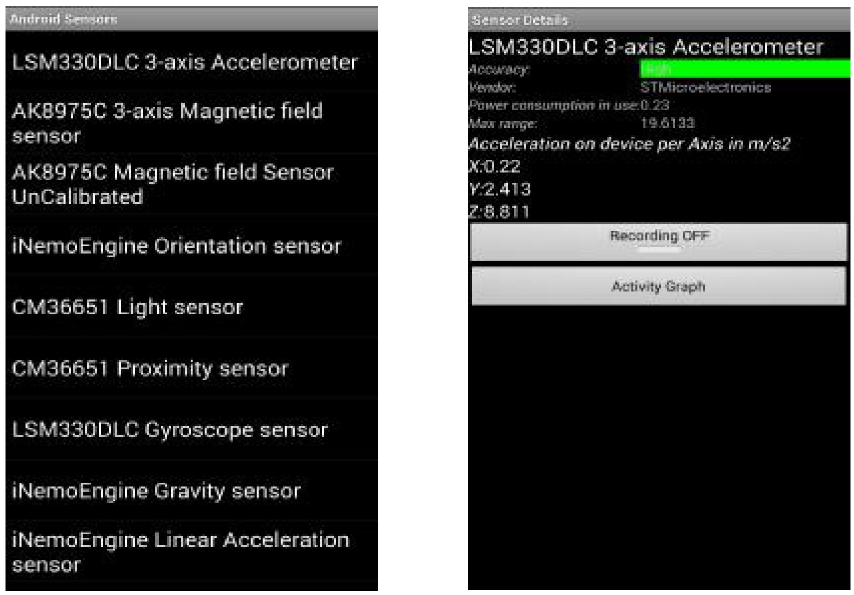


Figure 4.3 : List screen from Wi-Fi analyser application.

Figure (4.3) represents the list screen which shows the detected WAPs in a list. The MAC address, frequency and security capabilities are shown, in addition to the channel number, name and RSS for all WAP inside the building. A strength indicator with bars will go green for a good connection, orange for ok, and grey if signal strength is low (keuwl. 2013).

4.2.3 Sensors of Android Application

This application is used to record the readings of Smartphone sensors such as 3-axis accelerometer, orientation, magnetic field and so on (Vassilis, K., 2013).



(a) **(b)**

Figure 4.4 : The Screens for Sensors of Android Application.
(a) Android Sensors screen.
(b) Sensor Details screen.

The application has 2 separate screens: Android Sensors and Sensor Details. The Android Sensors screen which shown in Figure (4.) contains all sensors in Smartphone, and the information about sensor which shown in Figure(4.) such as accuracy, vendor, power consumption in use, max range and the sensor readings are shown in the Sensor Details screen in addition to two buttons Recording OFF and Activity Graph. When the Recording OFF button is pressed it turns into Recording On button and start to record the sensor readings in excel sheet until the Recording On button is pressed then stored it in Smartphone memory. In real experiments were conducted in our approach we used this application to collect the readings of 3-axis accelerometer sensor and the orientation sensor (Vassilis, K., 2013).

4.3 Experiments Results

In this section, we will discuss an analysis for each of the localization signature components, acceleration threshold, and average of the RSS values and a vector of all the possible directions inside the building section. Then the results of lookup algorithm will be presented.

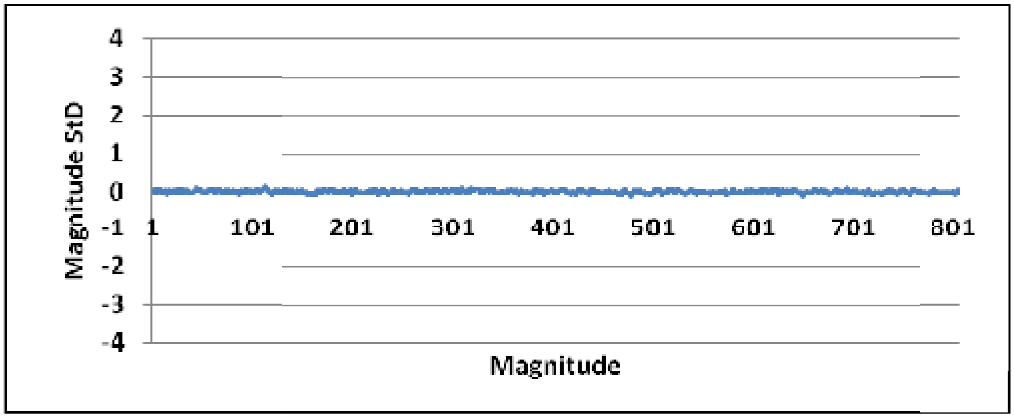
4.3.1 Acceleration Analysis

A premise of our approach regarding to the acceleration that the readings from 3-axis accelerometer sensor provides a means of inferring the user’s movement status, whether is moving or stationary. To prove that this premise is reasonable, Figures (4.4) and (4.5) show the representation of 800 values of magnitude, during time of window equals 8 seconds. The figures illustrate how can the results of St. D which vary between two types of sections (corridor and room) determines the user’s movement status, based on emergence and consistency of peaks.

The results of the 3-axis accelerometer readings (St. D), that resulted from online signature is compared with the acceleration threshold which is stored in the offline signatures, in order to determine the user’s movement status, whether is moving or stationary.

Acceleration is a vector which measures the change in the velocity for an object. So, if the user is stationary, the velocity will be fixed, thus the user's acceleration approximately closed to zero (Motion sensor. 2016). This is exemplified by Figure (4.5.a) and (4.5.b), where the St. D devolves to zero and this is good evidence which enables us to decide that the user’s movement status is stationary. In addition, there is a Peak Detection Algorithm (PDA) that uses acceleration to determine the number of user's steps, by counting the number of peaks during the movement of the user (Chon, Y., et al., 2012). So, the appearance of the peaks and the possibility of determining the number of user’s steps depending on these peaks indicate that the user is moving.

In Figure (4.5 a and b), there are no peaks, so if there is no indication to compute number of user's steps, then, the user's movement status is stationary. Therefore, the using of PDA is another evidence to prove that the user is stationary.

(a)


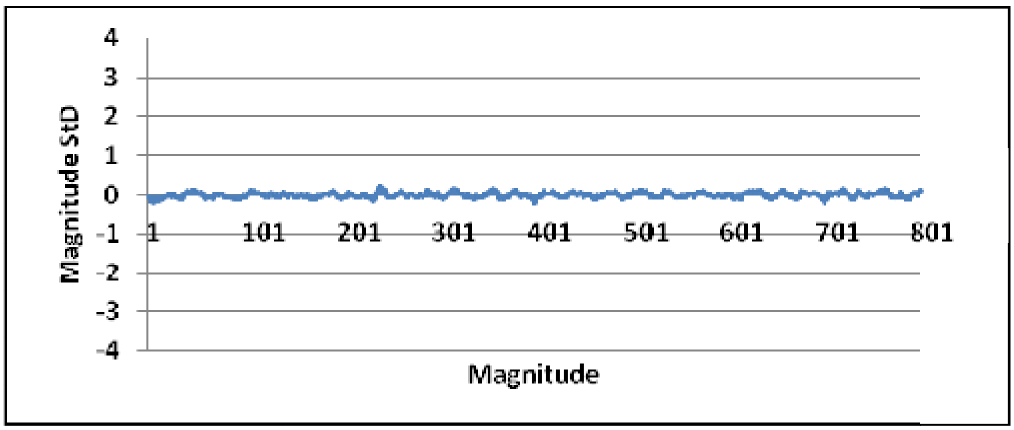
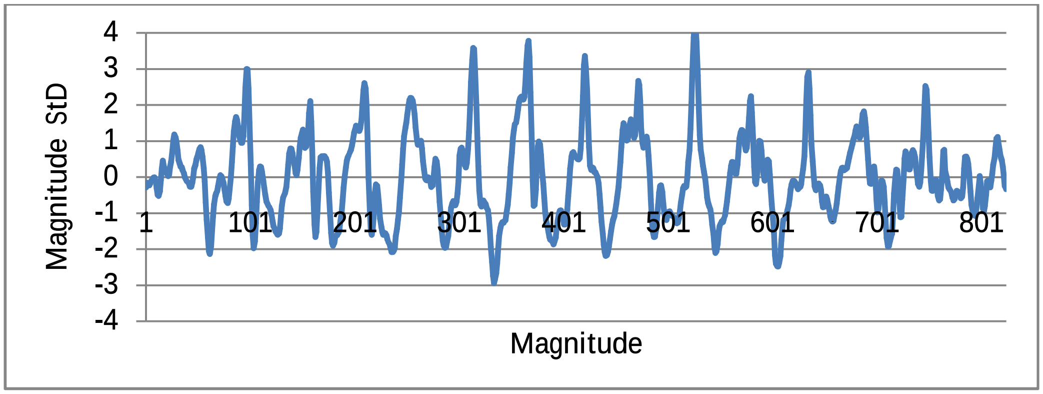
(b)


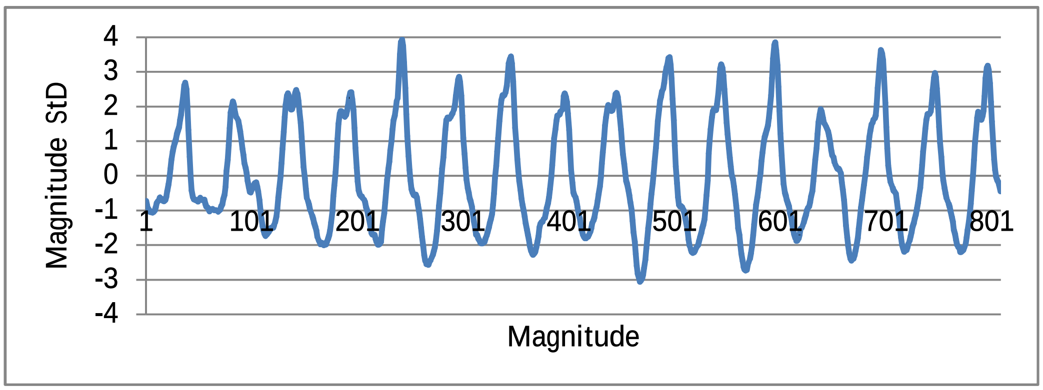
Figure 4.5: Standard deviation recorded in IT department,
(a) Represents the Magnitude StD when the user is stationary in Room1.
(b) Represents the Magnitude StD when the user is stationary in Corridor1.

Figure (4.6.a) and (4.6.b) illustrates the plot of St. D values, which is computed from 3-axis accelerometer when the user is moving inside the room or corridor. The values of St. D vary between -3 to 4 as presented in the figure, in both Room 1 and Corridor 1. So, the user acceleration is not fixed. This indicates that the user's velocity is not fixed. Thus, the acceleration is the variable, which proves that the user is moving. Also, depending on PDA, determining the number of user steps is possible, since there are peaks that appear in each room and corridor as shown in the figure. The possibility of

determining the number of steps is strong evidence that the user is moving inside a section.



(a)



(b)

Figure 4.6: Standard deviation recorded in IT department,
(a) Represents the St. D when the user moving inside room1.
(b) Represents the St. D when the user moving inside corridor.

The regularity of peaks is considered a good observation to determine that the user is walking inside a room or a corridor. The peaks that represent the user's movement inside room are irregular peaks due to the irregularity in the users' movements because of the obstacles available in the rooms which are more than the ones in the corridors. We can conclude that from Figure (4.6.a), through the emergence of inconsistent peaks which appears due to irrelevant user's movement, that produces because of hand shaking or obstacles that may have faced the user. As for the corridors, the peaks are regular compared with rooms. Figure (4.6.b) shows the regularity of peaks when the user is moving inside the corridor, the causes of this regularity, is that the possibility of facing obstacles in user's path inside a corridor is much lower than those that face him/her inside the room.

4.3.2 RSS Analysis

During the experiments in IT department and unit of admission and registration, the range of RSS is categorized according to the connection status consistent with IEEE standard (Veris Aerospond Wireless Sensors., 2013) as shown in Table (4.4). The signal quality in Table (4.4) indicates the connection status, and it is considered strong evidence which can be used to determine if the user is close or far away from AP. The higher RSS values, the closer the user from the AP.

Table 4.4: RSS levels

RSS range /dBm	Signal Quality
Over - 40	Exceptional
- 40 t0 -55	Very Good
- 56 to – 70	Good
- 71 to – 80	Marginal
Less -81	Intermittent to No Operation

In order to test whether the RSS values can be used as an indicator for detecting a user’s position according to the closest AP, we have conducted several real experiments, the results of two experiments of them are shown in Figures (4.7), (4.8).

Figures (4.7) and (4.8) show the representation of the average RSS for all APs during two experiments in the IT department, in Room1, Room2, and Corridor. The experiments were conducted in different environmental conditions and different times, where the first experiment is conducted in the case of students and staffs are moving inside a building, while the second experiment is conducted two weeks after the first experiment in different environmental conditions and times. It was observed that the average RSS values did not vary greatly between the two experiments as shown in the figures.

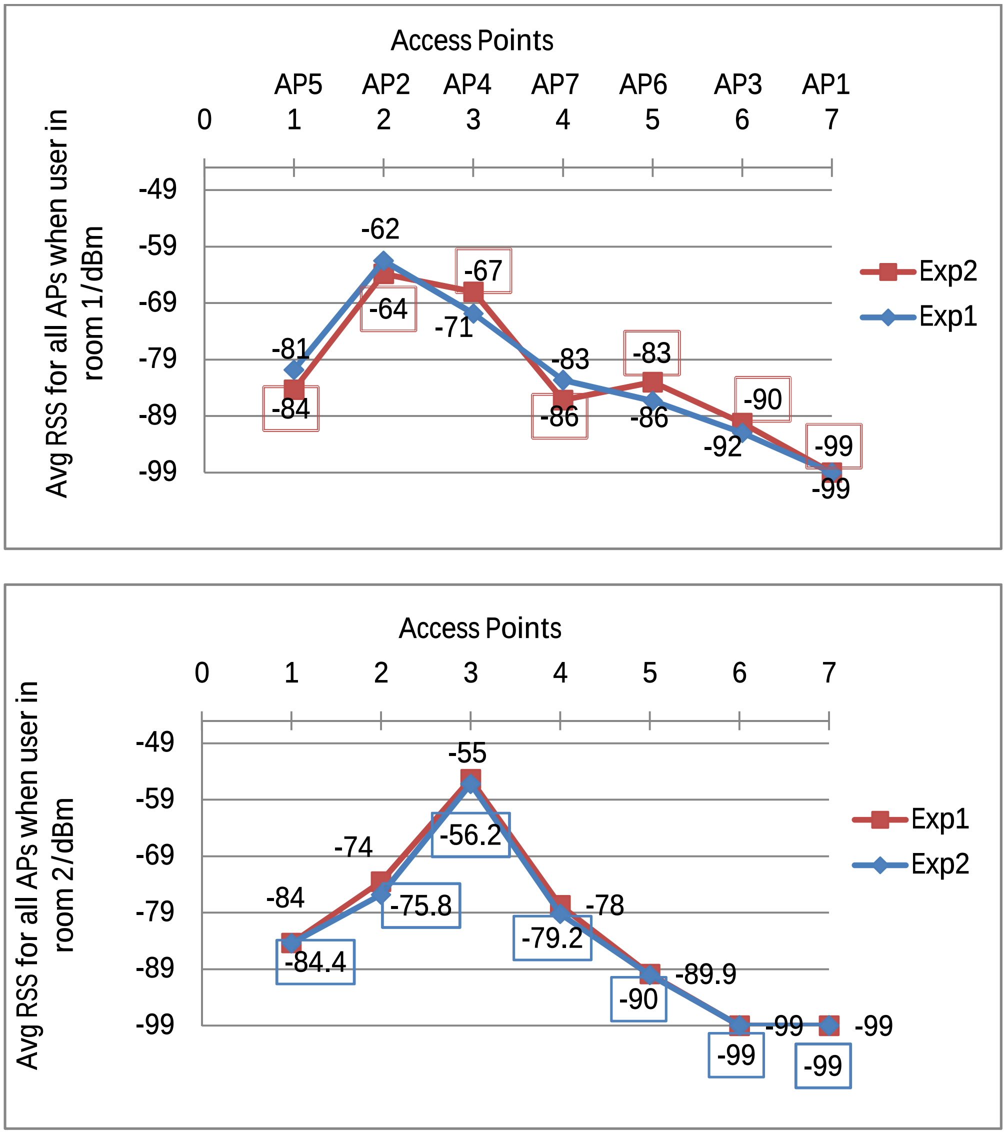


Figure 4.7: Avg (RSS) for all APs recorded in IT department during two experiments,
(a) represents the Avg (RSS) when the user is moving inside Room1.
(b) Represents the Avg (RSS) when the user is moving inside Room2.

From Figure (4.7), we can observe how the average of RSS which is recorded for each AP in both Room 1 and Room 2 during two experiments varies from section to section, according to the user's path inside these sections. It is worth mentioning, when the user is close to AP the RSS is strongest, and when the user is far away the RSS is weakest. This strong observation is an indication that uses the RSS as one of localization signature component to infer that the user's position leads to a promising accuracy.

The results in Figure (4.8) show that the nearest AP from Corridor 1 is AP4, while the farthest is AP1.

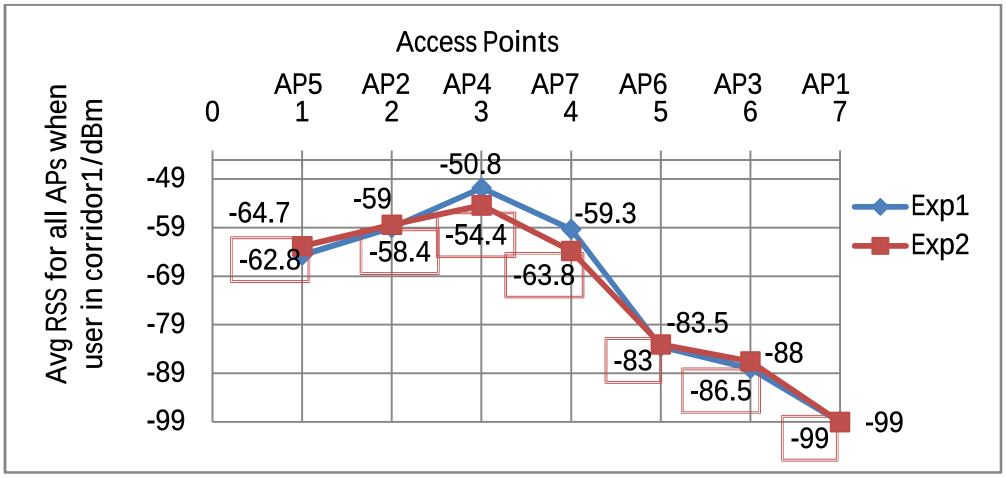


Figure 4.8: Avg (RSS) for all APs recorded in IT department during 2 experiment when the user moving inside corridor1

Results in Figures (4.7) and (4.8) indicate that there is no significant difference between first and second experiment, regarding to average of RSS that is represented in all sections, Room1, Room2 and Corridor1. (E.g. Figure (4.7.a) shows the greatest value of Average RSS for Room1 is recorded by AP2, but the lowest is recorded by AP1 in both experiments). This is consistent with what is shown in blueprint of IT department in Figure (4.1), where the nearest AP to Room 1 is AP2, and the farthest is AP1.

As a result of RSS analysis, we can conclude that RSS can be used to determine the user's location during the user's movement, depending on the locations of public APs. Although, the RSS values suffer from signal attenuation and multipath problems, however, computing average of RSS readings for the public APs contributes in reducing these problems. Moreover, the proposed approach could avoid the additional overhead of search process in database by depending on direction values from orientation sensor, in addition to the average (RSS), in order to determine the user's position and acquire promising accuracy.

4.3.3 Direction Analysis

The main step for detecting the direction values is to monitor the people's movement pattern when they enter into the sections (Room or corridor). The aim of this step is to limit all possible ways that are used to enter a section.

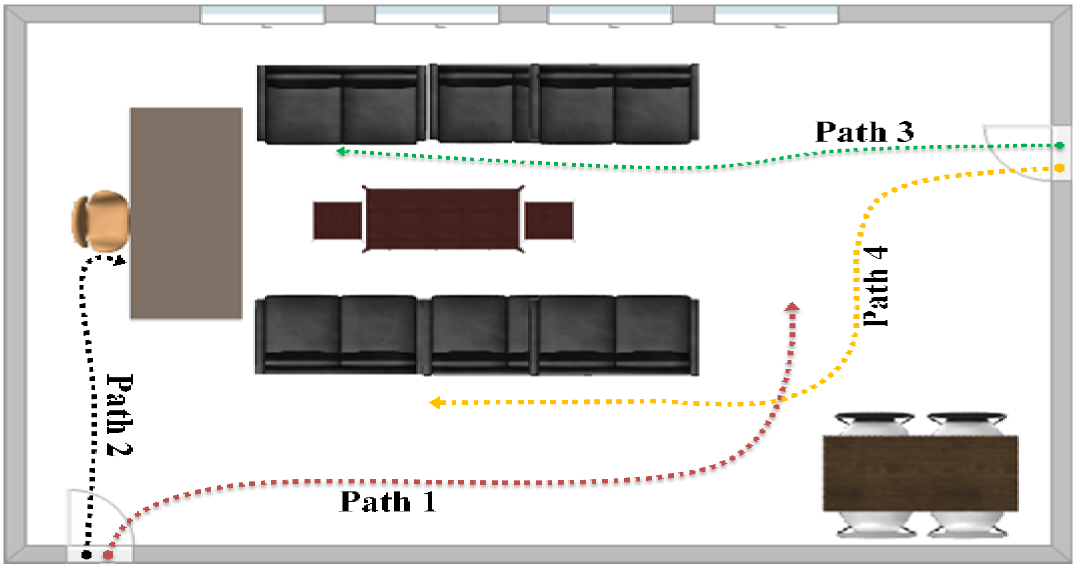


Figure 4.9: All possible paths inside Room1 in IT department – Offline phase

Figure (4.9) illustrates an example of monitoring people's movement pattern in Room 1 at IT department building, in order to detecting the paths that the user can be used to enter the room. So, these paths were surveyed by a surveyor in the offline phase, and then the results of directions are stored in the offline signature at signature map. When a user enters to the room, he/she can use one of the four paths that illustrated in the figure. Therefore, the room can be detected by observing the users' walking pattern.

Figure (4.10) shows a user's path, which may be used to enter Room1. From the figure, we observe that the user's path is close to path 1 which is shown in Figure (4.9).

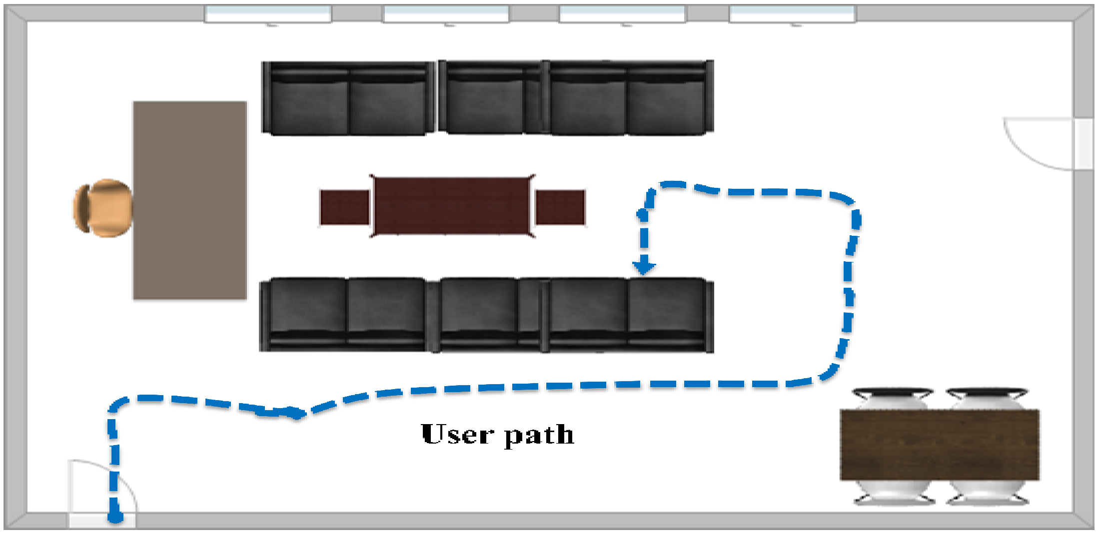


Figure 4.10: User's path inside Room1 in IT department – online phase

Table (4.5) shows the results of monitoring the direction of path 1 and path 2 which are presented in Figure (4.9), as well as the online user's path as shown in Figure (4.10).

Table 4.5: Direction values for user's path and 2 paths inside Room1 at IT department

User's Path	Path 1	Path 2
127 reading W	**95 reading W**	265 reading W
275 reading N	**399 reading N**	122 reading N
149 reading W	**240 reading W**	
169 reading S		
139 reading E		
Similarity	**83%**	**65%**

From Table (4.5), we can observe that the similarity between the user's path and path 1 is greater than the similarity between user's path and path 2. This indicates that when the user entered Room 1, he/she may uses path 1 according to the results.

I. Similarity Threshold Analysis

The similarity between sections which are located inside the building is computed by comparing directions of user's path from online signature, with directions for all stored paths from offline signatures, according to a path that has fewer directions number. If both values are similar, the output is true, otherwise it is false. Then, the summation of true values is divided on the number of directions, in order to acquire the similarity ratio.

In the proposed approach, the similarity threshold is determined according to the maximum results of comparing the direction of user's path from online signature, with the direction of stored paths from offline signatures for the same section, which are presented in Table (4.6).

Table (4.6) shows the results of real experiments were conducted in both, IT department and unity of admission and registration, in order to determine the similarity threshold. The columns in the table are:

- Section: represents a section where the user is located in during the online phase.
- Max similarity: represents the maximum similarity, which is resulting from comparison between the user's path from online signature and all stored paths from offline signatures for the same section.

Table 4.6: The maximum values of similarity ratio between user's path and stored paths for each section.

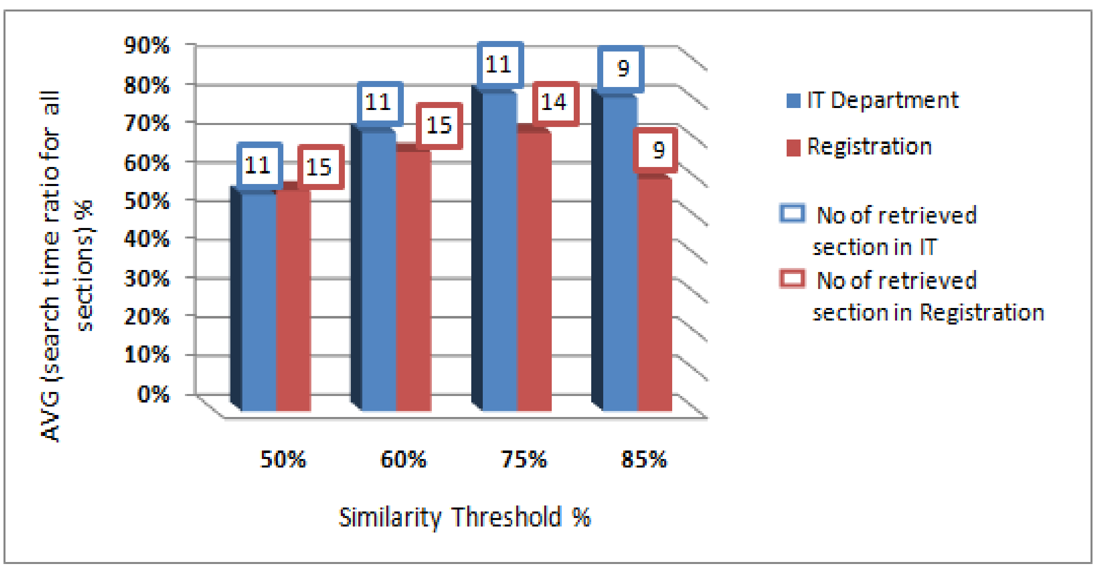
Unity of admission and registration		IT department	
Section	**Max similarity**	**Section**	**Max similarity**
Room1	0.91	Room1	0.83
Room2	0.83	Room2	0.95
Room3	0.92	Room3	0.78
Room4	1.00	Room4	0.87
Room5	0.77	Room5	0.85
Room6	0.79	Room6	0.89
Room7	0.92	Room7	0.98
Room8	0.78	Room8	1.00
Room9	1.00	Room9	0.9
Room10	0.64	Corr1	1.00
Room11	1.00	Corr2	1.00
Room12	1.00		
Room13	0.76		
Corr1	0.87		
Corr2	1.00		

From the Table (4.6), it can be observed that the minimum value of these maximum similarities is 64% at unity of admission and registration, and 78% at IT department. Therefore, the results in the Table (4.6) lead to select dynamic similarity threshold through conducting the experiments using different ratios greater and smaller than 64% and 78%, in order to identify the best similarity threshold that reduce the search time and retrieve all sections in the building. The result of these experiments is presented in Figure (4.11).

Figure (4.11) shows the results of experiments using the similarity of 50%, 60%, 75% and 85% as similarity threshold, the ratio to reduce the search time and the numbers of retrieved sections are as follows:

- When the similarity threshold is equal to 50% all sections in IT department are retrieved, and the search time is reduced by 56%. While at the admission and registration unit, all sections are retrieved, and the search time is reduced by 57%.
- When the similarity threshold is equal to 60% all sections in IT department are retrieved, and the search time is reduced by 72%, while at the admission and registration unit, all section are retrieved, and the search time is reduced by 67%.
- When the similarity threshold is equal to 75% all sections in IT department are retrieved, and the search time is reduced by 82%, while at the admission and registration unit, it did not retrieve all section.
- When the similarity threshold is equal to 85%, it did not retrieve all sections in both buildings.

Figure 4.11: The number of retrieved sections in different similarity threshold



From Figure (4.11) it can be concluded that the (60%) is the best similarity threshold value in admission and registration unit, according to the experiment results. While (75%) is the best similarity threshold value in IT department.

4.3.4 Localization Algorithm Results

This section presents and investigates the results that were achieved from conducting several real experiments, according to the proposed approach which is described in previous chapter. Mainly, results focus on enhancing conventional fingerprinting, using Smartphone sensors in addition to RSS, in order to determine the user’s position.

The results are described in two sections. The first section describes the experimental analysis outcomes of room detection phase, based on room level accuracy. The achieved goal of this phase is determine the user location in room level accuracy. The second section, represents the outcomes of experimental analysis of the position detection phase, which is responsible for detecting the user's position according to his/her location.

I. Phase 1: Room Detection

T he real experiments were performed using two scenarios. Scenario 1 was conducted in IT department building. Scenario 2 was conducted in the first and second floors of unity of admission and registration. In both scenarios, in the offline phase, the surveyor began from each section inside interested area, in order to form then store the offline signature for each section contains <A,R,D>. Also, in the online phase, the user began from any section. Then, the user entered inside this section to form the online signature <A, R, D>, in order to locate his/her position by comparing the online signature with all offline signatures that are stored in signature map.

As aforementioned, in the first stage of collection the RSS values, when the acceleration from online signature greater than acceleration threshold, the user is moving, then directions from online signature are used to reduce the number of retrieved sections, in order to reduce the amount of search time. Then the RSS average determines the user's location. Otherwise, when the acceleration from online signature is less the than acceleration threshold, the RSS average detects the user’s position in room level accuracy. In the second stage, the user’s position is determining in better accuracy by computing the distance using RSS average.

- **Stationary status**

A. Scenario 1 Results

The KNN algorithm is used to detect the user's location by using Euclidian Distance. Table (4.7) shows the distance values between average RSS from online signature and average RSS from offline signatures, for all sections in the IT department in case the user is stationary. From this table, we observe that the average of RSS can be used to infer the user's location by room level accuracy up to 100%. Since the minimum values that are shown in the last record in the table equals to the distance value between the average RSS in both signatures offline and online for the same section, but the room level accuracy alone is unpopular in indoor positioning, because of that, we will determine the user's position in better accuracy, in section(4.2.4.II) .

Table 4.7: Room detection in IT department using KNN

Room	1	2	3	4	5	6	7	8	9	Corr1	Corr2
1	8	21	26	21	26	49	54	55	58	37	69
2	22	3	42	33	15	63	65	66	67	35	79
3	27	43	6	20	48	37	43	46	54	42	49
4	15	31	17	7	33	46	53	52	55	36	62
5	29	13	50	39	8	68	71	70	68	39	84
6	51	63	34	41	64	5	29	17	29	70	34
7	54	66	40	47	67	24	6	22	37	75	42
8	57	68	47	50	65	16	28	8	18	80	45
9	57	66	50	48	62	29	36	22	6	81	51
Corr1	32	33	38	34	39	67	73	74	79	6	72
Corr2	68	78	48	55	80	31	39	34	42	78	10
MIN	**8**	**3**	**6**	**7**	**8**	**5**	**6**	**8**	**6**	**6**	**10**

From the result of comparing online signature for Room 1 with offline signatures for all sections, we find that the closest signature value is the value for Room 1. This observation proves that the average of RSS is a good indicator to determine the user location in high accuracy when the user's movement status is stationary.

B. Scenario 2 Results

Table (4.8) shows the distance values between RSS average from online signature and RSS average from offline signatures, for all sections in the unity of admission and registration in case the user is stationary. From table (4.8), it can be observed that the average of RSS estimates the user's location in room level accuracy to fourteen sections correctly out of fifteen sections. This means that the accuracy of determining the user's location is equal to 93%.

Table 4.8: Room detection in unity of admission and registration using KNN

Room	1	2	3	4	5	6	7	8	9	10	11	12	13	Corr1	Corr2
1	7	7	29	21	33	39	42	56	53	46	64	68	49	59	27
2	11	6	28	20	31	38	44	59	57	50	67	72	53	62	24
3	26	30	7	12	11	13	19	42	43	40	49	53	42	52	25
4	27	27	10	6	8	17	27	45	44	41	53	58	43	53	24
5	33	34	9	13	2	10	22	44	44	43	51	55	44	54	28
6	35	39	11	19	11	7	14	41	43	42	47	50	43	53	31
7	37	42	24	29	25	24	8	38	43	41	44	45	43	57	44
8	57	63	42	48	46	41	37	6	14	19	8	16	17	28	58
9	56	62	42	48	47	42	41	17	8	20	14	20	18	19	54
10	47	52	40	42	45	43	42	17	15	5	23	31	5	22	50
11	57	64	41	48	46	40	36	7	17	20	7	17	19	29	57
12	62	69	49	56	53	47	37	20	26	31	14	7	30	40	66
13	52	58	42	47	47	43	41	14	9	13	14	21	11	18	53
Corr1	51	56	41	45	46	42	45	20	15	11	23	33	12	12	48
Corr2	33	32	25	23	27	29	45	59	55	53	65	71	55	57	9
MIN	**7**	**6**	**7**	**6**	**2**	**7**	**8**	**6**	**8**	**5**	**7**	**7**	**5**	**12**	**9**

The environment layout could affect the result of the average RSS values. For instance, the differences between the average RSS values in scenario 1 are greater than the ones in scenario 2.

For an example, Room13 and Room 10 are opposite rooms as shown in Figure (4.12), therefore, when the user is in Room 13, the algorithm which uses RSS to detect the position decides that the user is in Room 10.

The algorithm which uses direction as well as RSS overcomes this problem, because if the rooms are opposite and have the same RSS value, they differentially have different directions.

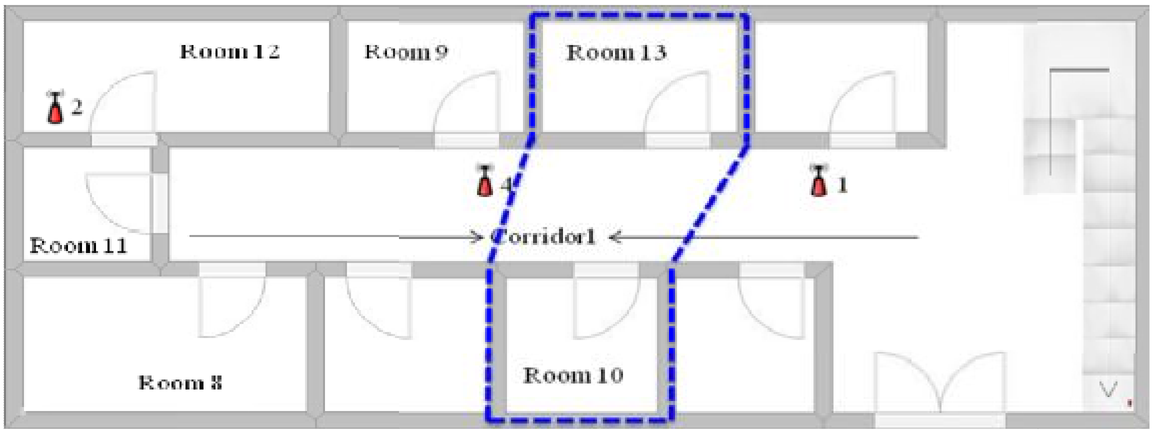


Figure 4.12: Blueprint for 1st floor in unity of admission and registration represents opposite rooms (Room 10, Room 13)

- **Movement Status**

Based on the proposed approach, when the user who wants to localize his/her position moves inside the building, the values of his/her direction should be used to determine his/her position, with high accuracy. The direction values are used in two methods to determine the user's position. The first method uses the values of direction with RSS while the second method uses the values of direction.

A. The First Method Results

According to lookup algorithm, when the first method is used, the values of direction are used to limit the number of retrieved sections, in order to reduce the time consumed for the search and comparison processes. Then the average of RSS is used to locate the user in room level accuracy.

When the user enters any section and intends to locate his/her location, the online signature is formed as follow <A, R, D>. Where A identifies that user is moving, D determines the retrieved sections, and R detects the user's position in room level accuracy by comparing it with R for all sections which are retrieved.

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Figures (4.13) and (4.14) show the number of retrieved sections in IT department and unity of admission and registration respectively. From these figures, we can observe that the highest value for number of retrieved sections did not exceed three sections in IT department, and seven sections in unity of admission and registration. This means that the directions can reduce the time which is spent to locate the user in a percentages ranging between 73% - 91% in IT department, where the average for all sections is 82%. While the range is between 53% to 93% in unity of admission and registration, and the average for all sections is 67%. These percentages are presented in Tables (4.9) and (4.10).

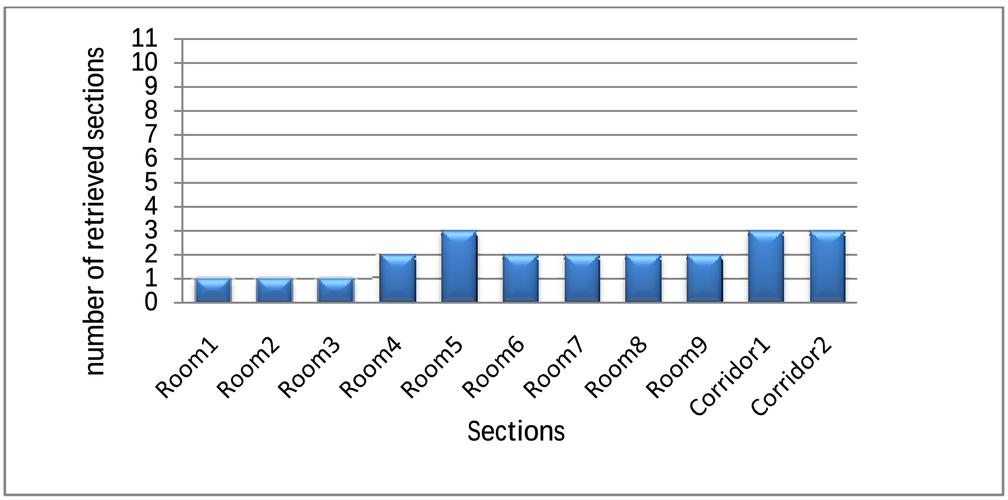


Figure 4.13: Number of retrieved sections in IT department building

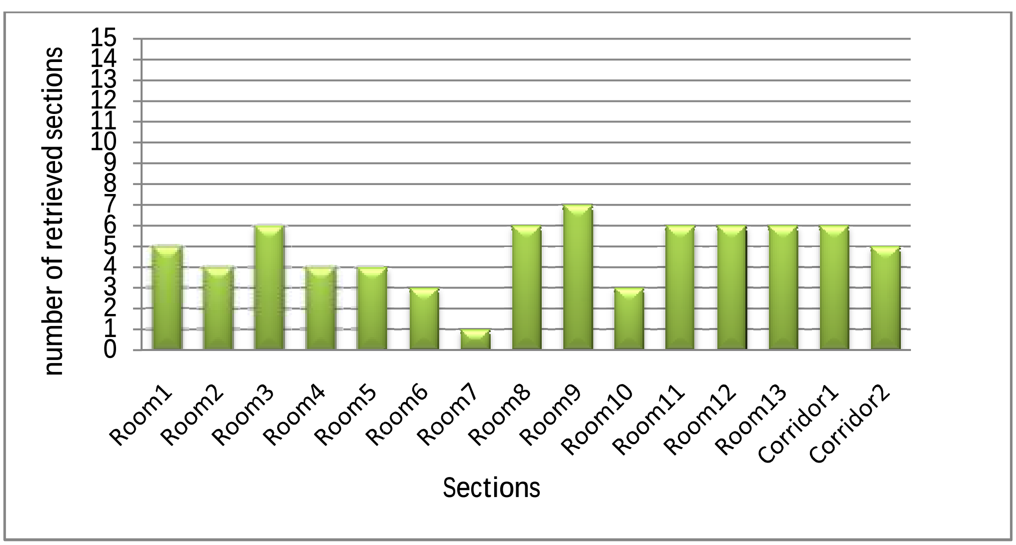


Figure 4.14: Number of retrieved sections in unity of admission and registration building

Figure (4.13) presents the number of retrieved sections, which is resulting from computing the similarity between each section with all sections in IT department, then limit the sections that are have the similarity greater than or equal to empirical similarity threshold in order to obtain the number of these sections. Figure (4.14) presents the number of retrieved sections in the unit of admission and registration.

Table 4.9: The results depending on directions values when similarity threshold =75% in IT department

Section	No of retrieved sections	Retrieved sections	Ratios of reducing the time
Room 1	1	Room**1**	0.91
Room 2	1	Room**2**	0.91
Room 3	1	Room**3**	0.91
Room 4	2	Room (**4**,5)	0.82
Room 5	3	Room (4,**5**)	0.82
Room 6	2	Room (**6**,9)	0.82
Room 7	2	Room (**7**,8)	0.82
Room 8	2	Room (7,**8**)	0.82
Room 9	2	Room (6,**9**)	0.82
Corridor 1	3	Room (6,9) and **Corridor1**	0.73
Corridor 2	3	Room (4,5) and **Corridor2**	0.73
Average			**0.82**

Table 4.10: The results depending on directions when similarity threshold =60% in unity of admission and registration

Section	No of retrieved sections	Retrieved sections	Ratios of reducing the time
Room 1	5	Room (**1**,3,6,9,12)	0.67
Room 2	4	Room (**2,**4,5,10)	0.73
Room 3	6	Room (1,**3**,6,9,12,13)	0.60
Room 4	4	Room (2,**4**,5,10)	0.73
Room 5	4	Room (2,4,**5**,10)	0.73
Room 6	3	Room (3,**6**,9)	0.80
Room 7	1	Room (**7**)	0.93
Room 8	6	Room (5,**8**,11,12) and Corridor (1,2)	0.60
Room 9	7	Room (1,3,6,7,**9**,12,13)	0.53
Room 10	3	Room (5,8,**10**)	0.80
Room 11	6	Room (8,10,**11**,12) and Corridor (1,2)	0.60
Room 12	6	Room (1,3,6,9,**12**,13)	0.60
Room 13	6	Room (1,3,6,9,12,**13**)	0.60
Corridor 1	6	Room(3,8,11,12) and **Corridor**(**1**,2)	0.60
Corridor 2	5	Room (8,11,12) and **Corridor** (1,**2**)	0.67
Average			**0.67**

Tables (4.9) and (4.10) show the results of comparing the direction values from online signature for each section, with directions values from offline signatures for all sections. Similarity threshold is equal to 75% in IT department, and 60% in unity of admission and registration. The columns in the tables are:

- Section: represents the section where a user is located in during the online phase.

- No of retrieved section: represents the number of retrieved sections after performing the RSS_ Direction algorithm, which is used to limit the number of retrieved sections and reduce the amount of search and comparison processes time.

- Retrieved sections: represents the sections which are retrieved as a result of comparing the directions of user's path from online signature for each section, with the directions of all sections paths from offline signatures.

- Ratios of reducing the time: represents the percentages of saving the search and comparison time by reducing the number of retrieved sections.

When the user is stationary, the comparison process is applied on all sections, but when the user is moving, the comparison process is applied just on the retrieved sections. So the time of search and comparison is reduced based on the user's direction, (e.g. retrieved sections that corresponds to Room 4 in unity of admission and registration as shown in Table (4.10) is equal to 4, so the percentage of reducing the time approximately equal to 73%).

After selecting the sections which are retrieved, the user's position in room level accuracy is determined by average RSS as explained in stationary status part. We conducted the comparison process when the user is moving just on sections that were retrieved. Based on room level accuracy in this case, the result is better than the result when the user is stationary. Because, using the similarity threshold to retrieve the sections, it excludes one of the opposite rooms, so the average RSS determines exactly the user's position depending on room level accuracy.

An example illustrates that using the direction then RSS to locate the user is more accurate than using only RSS. When using only RSS, Room 13 and Room 10 are opposite rooms, therefore when the user is inside Room13, the algorithm decides that the user is in Room10. The reason is that most of the

time, the opposite rooms have the same distance from the APs, which means they could have the same RSS averages. In the second method, we observe that the retrieved sections from comparing Room 13 directions with directions of all sections which is shown in Table (4.10) is, Rooms (1,3,6,9,12,13), these results exclude Room10. So, the nearest neighbour from Rooms (1, 3, 6, 9, 12, and 13) is Room 13 and this is the required result.

Consequently, using directions values with average RSS have an ability to give exact position in room level accuracy when the user is moving inside a building, because they can overcome the problem of the opposite rooms.

B. The second method results

Using the second method, we just depend on direction values to detect the user's position in room level accuracy.

Tables (4.11) and (4.12) show the results of dependence on directions values to locate the user in a room level accuracy, in building, IT department and unity of admission and registration. The columns in table are:

- Section I: represents the section where the user is located in during online phase.
- Max similarity (section I): represents the maximum similarity resulted from comparing the user's path from online signature with all stored paths from offline signatures for the same section.
- Max similarity (section I, All sections): represents the maximum similarity resulted from comparing a user's path from online signature with all stored paths from offline signatures for all sections.
- Result: represents the user's location in room level accuracy resulted from retrieving the section that is equal to Max similarity (section I, All sections).

Table 4.11: Max similarity between user's path and all stored paths for the same section – IT department

Section I	MAX Similarity (section I)	MAX Similarity (section I, All sections)	Result
Room 1	**0.83**	**0.83**	**Room 1**
Room 2	**0.95**	**0.95**	**Room 2**
Room 3	**0.78**	**0.78**	**Room 3**
Room 4	0.87	0.91	Room 5
Room 5	0.85	0.86	Room 4
Room 6	**0.89**	**0.89**	**Room 6**
Room 7	**0.98**	**0.98**	**Room 7**
Room 8	1.00	1.00	Room 8,7
Room 9	**0.9**	**0.9**	**Room 9**
Corridor1	**1.00**	**1.00**	**Corridor 1**
Corridor	**1.00**	**1.00**	**Corridor 2**

Table 4.12: Max similarity between user's path and all stored paths for the same section – unity of admission and registration

Section I	MAX Similarity (section I)	MAX Similarity (section I, All sections)	Result
Room 1	**0.91**	**0.91**	**Room1**
Room 2	0.83	0.83	Room (2,10)
Room 3	0.92	0.92	Room (1,3,9,12,13)
Room 4	1.00	1.00	Room (2,4,5,10)
Room 5	0.77	1.00	Room (2,4,10)
Room 6	0.79	0.83	Room 3
Room 7	**0.92**	**0.92**	**Room 7**
Room 8	**0.8**	**0.98**	**Room 8**
Room 9	1.00	1.00	Room (1,3,6,9,12)
Room10	0.64	0.98	Room 8
Room 11	**1.00**	**1.00**	**Room 11**
Room 12	1.00	1.00	Room (1,3,9,12,13)
Room 13	0.76	0.98	Room 9
Corridor1	**0.89**	**0.89**	**Corridor 1**
Corridor 2	1.00	1.00	Corridor (1,2)

The findings of determining the user's position in room level accuracy depending only on the values of direction are presented in Table (4.13) for both buildings. While our approach uses the direction as an indicator to infer the user's location in room level accuracy up to 73% to retrieve exact section in IT department, and 33% in unity of admission and registration.

Table 4.13: Summary results of determining the user's location depending only on direction

Building		Exact Section	Multiple sections	False detection
IT department	**Section**	8/11	1/11	2/11
Admission & registration	**Section**	5/15	6/15	4/15

The conclusion from investigating and testing the results of room detection phase, the room level accuracy is insufficient in positioning field. So, the proposed approach should determine the user's position depend on better accuracy, which is presented in (Section 4.2.4.II).

II. Phase 2:- Position Detection

This subsection introduces the result of the real experiments of detecting the user's position in IT department. Table (4.14) shows the acquired results.

Table 4.14: Results of user's position detection – IT department

Room I	Avg(RSS)				
	LM	**User's location inside Room i**	**Estimated distance**	**Real distance**	**Error ratio**
Room 1	-74	-76	1.29517	2.19	0.895
Room 2	-74	-75	1.08041	1.657	0.576
Room 3	-73	-75	1.31027	3.157	1.846
Room 4	-75	-78	1.4132	3.18	1.767
Room 5	-69	-48	1.64757	4.447	2.799
Room 6	-72	-76	1.58521	3.613	2.028
Room 8	-78	-76	1.28462	1.503	0.219
Room 9	-83	-81	1.29966	3.66	2.36
Co1	-67	-60	2.30182	3.693	1.392
Co2	-66	-68	1.54205	4.447	2.905

Table (4.14) shows the results of user's position detection in IT department, where the accuracy of detecting the user's position, equal to the average of the estimated distance for all sections, which is equal to 1.48m, and standard deviation is 0.34. The columns in the table are:

- Room I: represents the room which a user was located in during he/she wants to detect his/her position.

- Avg (RSS) for LM: represents the average of RSS readings when surveyor stands on a landmark, which is stored in the database from offline phase.
- Avg (RSS) for the user's location inside Room I: represents the average of RSS readings for the user's location inside Room I, after the user's location in room level accuracy is determined.
- Estimated distance: represents the distance between the user and the landmark, which is computed using Equation (3.3), depending on Avg (RSS) for landmark and Avg (RSS) for the user's location inside Room I.
- Real distance: represents the distance between the user and landmark, which was computed by the surveyor, in order to determine the error ratio of the proposed approach.
- Error ratio: represents the difference between real distance and estimated distance.

So depending on the proposed approach, the user can get her/his position within a circle of 1.48 m radius.

4.4 Error Analysis

The outcomes of our real experiments refers that there are some errors in room detection phase and position detection phase. In this part, the error analysis for both phases is presented. Then, the system robustness findings are displayed.

4.4.1 Room Detection Accuracy

In order to test the accuracy of room detection phase, we have carried out several real experiments in both cases, whether the user is stationary or moving, and the outcomes are discussed below.

I. Stationary Status

The real experiments which were performed in IT department in this status conducted at different times and different environmental conditions. However, it gave exact section in most experiments. The reason is that, the opposite rooms inside IT department are different in size and design, thus, the average of RSS will be different from section to section, and will be unique signature for each section. So, the average of RSS has an excellent ability to determine the user's location in room level accuracy. While the real experiments were carried out in unity of admission and registration have an error ratio. The

reason is that, the opposite sections in this building have similar size and design, which means they have similar distance between them and the APs, so the averages of RSS for these section are convergent.

From ten real experiments which were carried out to detect an error rate, it can be concluded that the ratio of error in IT department is ranging from 0% to 9% with average error of 4%. While, the error rate in unity of admission and registration is ranging from 0% to 20% with average error of 11%.

II. Movement status

In order to test the influences of user’s direction in detecting the user’s position in room level accuracy, we have conducted an experiment and the results are presented in Table (4.13). The table presents the number of sections which did not give exact section, which is equal 3 in IT department and 10 in unity of admission and registration. This means, the error ratios when using only the user's direction to determine user’s location in room level accuracy are 18% and 67% respectively.

4.4.2 Positioning Accuracy

The outcomes of our real experiments refer that there are ratio of error between the estimated and real locations, which arise from the variability when measuring the estimated distance. The error of our approach can be obtained by computing the difference between the proposed approach's position and the real position.

From Table (4.14) the average error can be computed using Equation (4.1). For the proposed approach the average error is 1.7m, and the standard deviation is 0.9.

Position average error =AVG (Real Distance) - AVG (Estimated Distance) Equation (4.1)

Where,
AVG (Real Distance): Average of real distance.
AVG (Estimated Distance): Average of estimated distance.

4.4.3 Robustness

Considering only the room level accuracy when all APs are active, is not enough to test the proposed approach robustness.

Table 4.15: Results of the proposed approach robustness

	IT department		Admission and registration	
Experiment ID	**Number of active APs**	**Room level accuracy**	**Number of active APs**	**Room level accuracy**
1	7	100%	5	93%
2	6	100%	4	80%
3	5	100%	3	67%
4	4	91%	2	60%
5	3	82%		
6	2	82%		
Average		93%		75%

Therefore, the user's position when one or more AP are disrupted, which means how consistently the proposed approach works, can be used to determine the robustness of the proposed approach. It can be determined by conducting new real experiments, and at least disrupt one AP in each experiment, until the system's reliance on two APs to detect the user's position. The findings of these real experiments are shown in Table (4.15).

The summary of Table (4.15) results is that the accuracy of detecting the user’s position inside IT department is ranging between 82% - 100%, with average error of 7%. While inside the unit of admission and registration, the accuracy of detecting user’s position is ranging between 60% - 93%, with average error of 25%. The reason of that, the APs have a well distributed form, and then the signal attenuation problems and multipath can reduced.

4.5 Comparisons

In this section, the comparison between the proposed approach and fingerprinting approaches is presented by comparing the proposed approach with some existing fingerprinting approaches in terms of the following:

- **Database size**: the proposed approach collects the offline signature components during the surveying as presented in (Chapter 3). Ultimately, the signature map of proposed approach (database) contains a signature

for each section in the building which consists of, (acceleration threshold, number of directions for each expected paths that the user can used it to enter a section, and average RSS for each AP). It means that the signature map is very small compared to fingerprinting approach, which requiring long period of time in order to collect the data (at least between 20 to 30 fingerprints for each marked place).

- **Database calibration**: in order to build the radio map database using fingerprinting technique, it requires collecting the readings from time to time because of any changes in the environment, such as installing a new AP. In contrast, the proposed approach uses directions values to minimize the reliance on RSS readings, and to reduce the calibration. In addition, in the proposed approach, the APs are distributed inside a building depending on the well topological form, in order to overcome the multipath and the signal attenuation problems as much as possible. So, with reliance on directions to determine the location, calibration process has been reduced to the highest extent, as long as the AP have the same location that were identified when the experiments were conducted, even if new AP is installed, because based on the proposed approach, the data for signatures components is collected only from those APs that are stored in a database.

- **Energy and time**: with regard to time and energy which are consumed in locating the user, we have measured the time and energy for the proposed approach in order to compare it with some fingerprinting approaches.

  Concerning energy, the energy which is consumed for surveying the building in the proposed approach is low (e.g., 0.64 Watt (W) in unity of admission and registration), knowing that the capacity of Smartphone battery which is used to collect a data equals 7.98 W. Also, the consumed energy for localization is very low, because all signature components are collected at the same time, and the search algorithm is linear. In contrast, the energy which is consumed for surveying the building in RADAR is high energy, due to the huge number of fingerprints that were collected. As for time measurements, the proposed approach needs few minutes for surveying the building, because all signature components are collected at the same time. While, RADAR needs a long period of time for surveying the building in order to collect the fingerprints. But, in the localization most of fingerprinting approaches do not need more than a few seconds to determine the user's location.

- **Accuracy**: the accuracy of proposed approach is ranging between 1.5 to 3 m, while the accuracy of RADAR system between 3 to 5 m. Though some fingerprinting approaches have better accuracy, but, the number of fingerprints is increased, thus the time of surveying and rebuilding the database are affected.

Table (4.16) summaries the comparison results between the proposed approach and some other fingerprinting approaches.

Table 4.16. Comparison results between the proposed approach and other fingerprinting approaches.

Approach	Database Size	Database Calibration	Energy and Time	Accuracy
The proposed approach	Few record for each room signature	Calibration process has been reduced to the highest extent with reliance on directions.	Few minutes for surveying, few seconds for localization.	- Room level 97% - (1.5 – 3) m
ARIEL	193 positions X 20 measurements in each marked place	Every few months	Few minutes for surveying, few seconds for localization.	Room level 95%
Peer Assistance	131 positions X 20 measurements in each marked place	Every few months	Few minutes for surveying, Few seconds for localization.	(2 – 3) m
RADAR	70 positions X 30 measurements in each marked place	Every few months	few minutes for surveying, Few seconds for localization.	(3 – 5) m
WILL	- Fingerprint database - Floor plan database	Automatically	Without surveying, few seconds for localization.	Room level 86%

4.6 Summary

The proposed localization approach provides room level accuracy of 97% in two different buildings, and detects the position with error of 1.5 to 3 m.

Depending on the direction to determine the location, calibration process has been reduced to the highest extent, as long as the AP have the same locations that were identified when the experiments were conducted, even if a new AP is installed.

4.7 Conclusion

The thesis presents an indoor localization approach that addresses the limitations of fingerprinting technique. The proposed approach constructs a signature map which contains a unique signature for each section inside the building called offline signature. The offline signature is built in offline phase by recording the readings of acceleration, direction, and RSS during a survey for each section inside the building. Based on that, the user is able to find his/her position by comparing the online signature, which is formed in the online phase with offline signatures.

In order to minimize the size of the database and the effort of building the database, each section correspond a few records in the database. In addition, based on similarity threshold, the direction is used to minimize the size of the database and reduce the amount of search time that is used to determine the user's position. Moreover, the effort of building the database is minimized by surveying each section inside building for one time, based on all expected paths in each of them; this in turn reduces the calibration process which is considered as one of fingerprinting technique problems that required a lot of time and effort to rebuild the database from time to time. In order to solve the Wi-Fi RSS problems, the recording RSS values are restricted only on the public APs which are stored in the database. Furthermore, the average of RSS values is computed to minimize the effect of noisy RSS values and multipath signal attenuation problems.

The results of acceleration and direction readings are combined with RSS to acquire a promising and accurate position. The acceleration values which are collected from 3-axis accelerometer are used to compute the standard deviation in order to detect the user's movement status. While, the user's direction is estimated using orientation sensor then it's used with RSS in order to minimize the calibration, solve the opposite room problem, and reduce the time and effort which are used to detect the users' positions.

In order to overcome the issues of the noisy sensors, the gravity force from acceleration readings is excluded by computing the magnitude for each reading to determine the user's movement status. As for orientation sensor, the direction values are estimated for four directions (W, E, S and N) in order to reduce the error rate

regarding to user's direction. Moreover, using the concept of sensor fusion is one of the strong points to overcome the issues of noisy sensor.

The real experiments were conducted based on the proposed approach in two different environments. They showed that the accuracy of determining users' positions is approximately 97% in room level accuracy, and the distance estimation had a mean error of 1.48 m. So depending on the proposed approach, the users can get their positions within a circle with a radius of 1.48 m.

4.8 Future Work

One of the limitations of this work is detecting accurate direction; therefore, we assume that the user holds the Smartphone by hand. In the future work, we will consider the direction estimation in all cases even if the user does not hold the Smartphone by hand.

In addition, special attention will be given to enhance the fingerprinting technique taking into account building the physical map dynamically rather than RM because using the dynamic physical map for the building instead of build the RM will avoid the recalibration that are usually required in fingerprinting based approaches due to signal attenuation or scattering.

The location of the APs in the proposed approach should be defined in advance. In the future work, this issue should be resolved to make the system more robust and able to be generalized.

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